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REPORT ON THE EVALUATION OF DEMAND FORECASTING  
TECHNIQUES FOR THE SUBSISTENCE COMMODITY VOLNE 1(U)

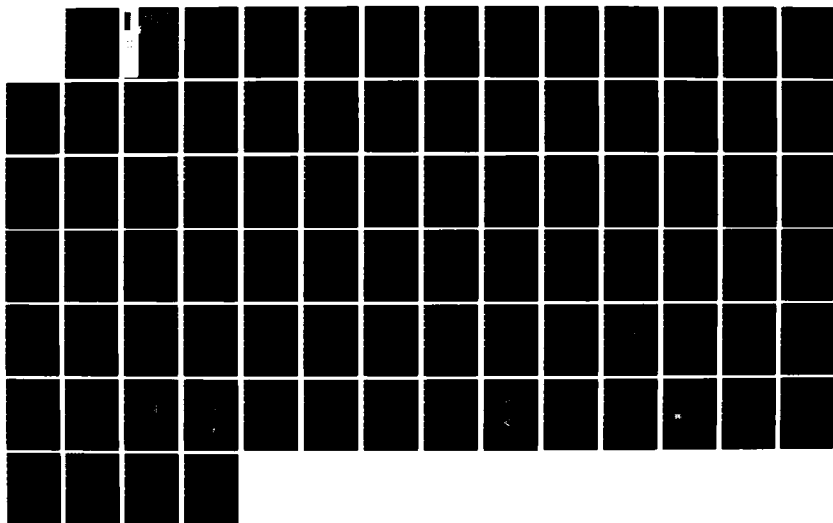
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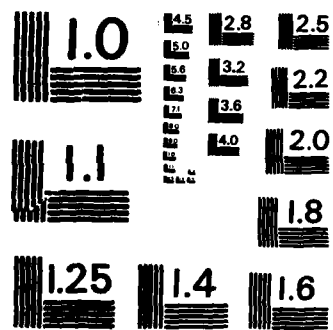
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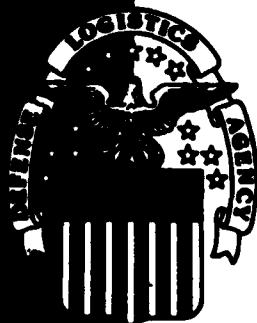
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Report on the Evaluation of Demand Forecasting  
Techniques for the Subsistence Commodity  
Volume I of II

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Per Ms. Cleo Ridgeway, Defense Logistics  
Agency/LO

October 1985

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Thomas J. Sheehan  
DLA Operations Research and Economic Analysis Office  
Headquarters, Defense Logistics Agency  
Cameron Station, Alexandria, Virginia

Major Larry D. Heck, USA  
Defense Integrated Subsistence Management System (DISMS) Task Group  
Defense Personnel Support Center  
Philadelphia, Pennsylvania

Dr. David Rothenberg, President  
Inductive Inference, Incorporated  
New York, New York

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## DEFENSE LOGISTICS AGENCY

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ALEXANDRIA, VIRGINIA 22314

### FOREWORD

*Start*  
This study involves the evaluation of quantitative techniques to improve subsistence demand forecasting in the Defense Logistics Agency. A wide variety of techniques were tested for approximately 4,000 item/warehouse demand series over the 1977-1983 time frame.

The range of forecasting techniques analyzed included the following: autoregressions, autoregressions with seasonal terms: simple moving averages; single, double, adaptive and combined exponential smoothing; naive and the current DLA methods. The methodology, in effect, substituted individual and/or groups of methods for the DLA method to compute forecasts over the 1980-1983 period.

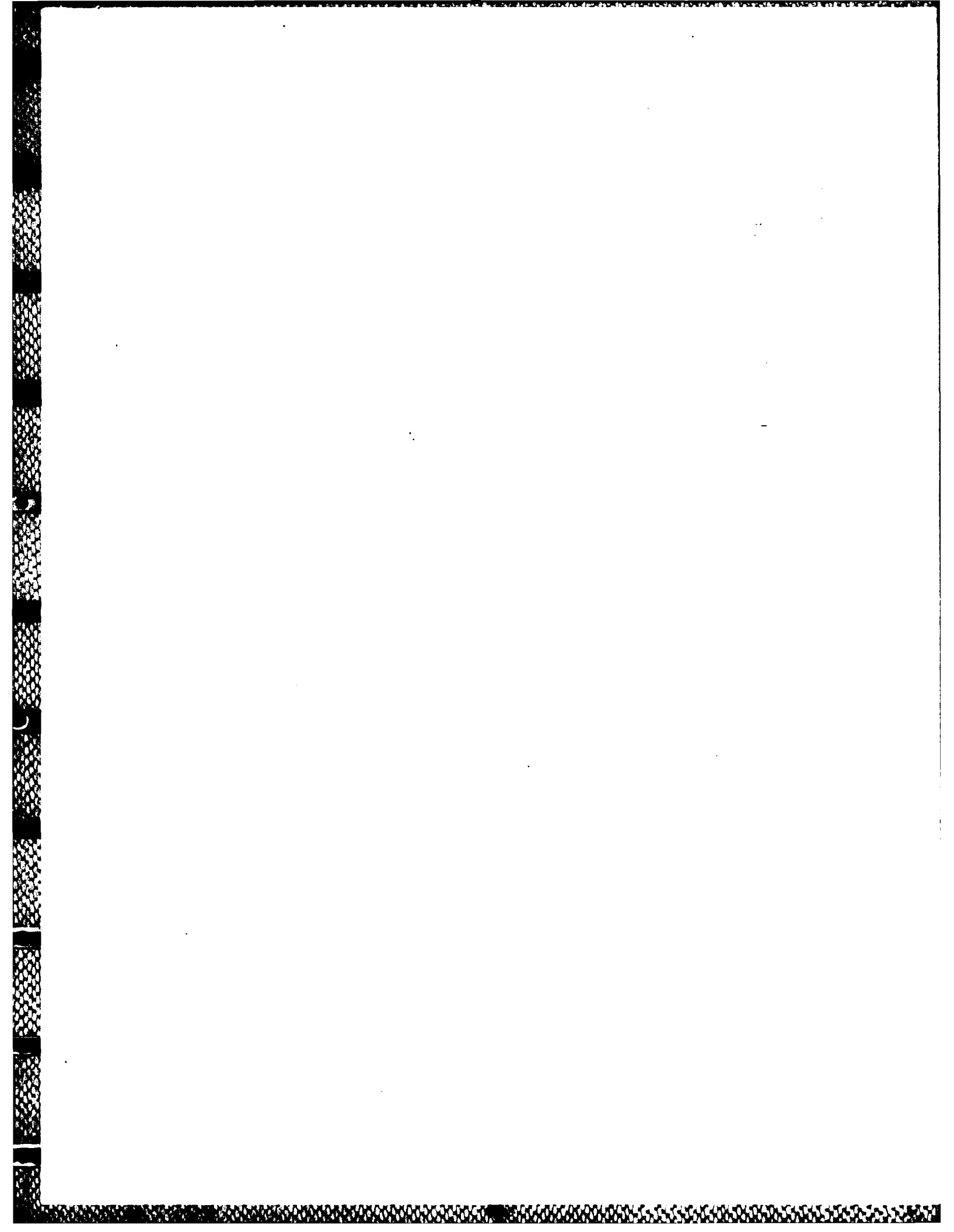
Findings indicated that about 20% more variability in lead time demand was incurred during the 1980-1983 time period than achieved by a group of five methods identified in this study, during that period. Similarly, 14% more variability in procurement cycle demand forecast error was incurred during the 1980-1983 time period.

Procedures are identified that can achieve further substantial reductions in variability of lead time demand through the use of forecast adjustments. A prototype subsistence demand forecasting system is described based on the recommended group of models in this study. This study also serves as the analytical basis for the development of the functional description for the Forecasting Module of Defense Integrated Subsistence Management System (DISMS).

Volume I contains the body of the study report, while Volume II provides amplifying details in appendices.

The effort documented herein was a study; its findings and conclusions reflect the data at the time the study was conducted and should not be construed as the official position of the Defense Logistics Agency.

  
ROGER S. NOR  
Acting Assistant Director  
Policy and Plans



## Acknowledgements

This study was conducted with a team of highly dedicated and professional personnel from government and industry. The authors wish to express grateful acknowledgement to each member of the team and to recognize those whose help was especially instrumental to the study:

### Team Participant

Mr. John Ferguson, HQ, Defense Logistics Agency  
Mr. Frank Pender, HQ, Defense Logistics Agency  
Mr. Vic Schwartz, Defense Personnel Support Center  
Mr. Nick Marino, Defense Personnel Support Center  
Mr. Jim Romano, Defense Personnel Support Center  
Mr. Harry Rutherford, Defense Personnel Support Center

Ms. Saryud Devchand, Inductive Inference, Inc.  
Ms. Jane Loeb, Inductive Inference, Inc.  
Ms. Sue Suhasny, Inductive Inference, Inc.

Ms. Gail White, Advanced Technology, Inc.

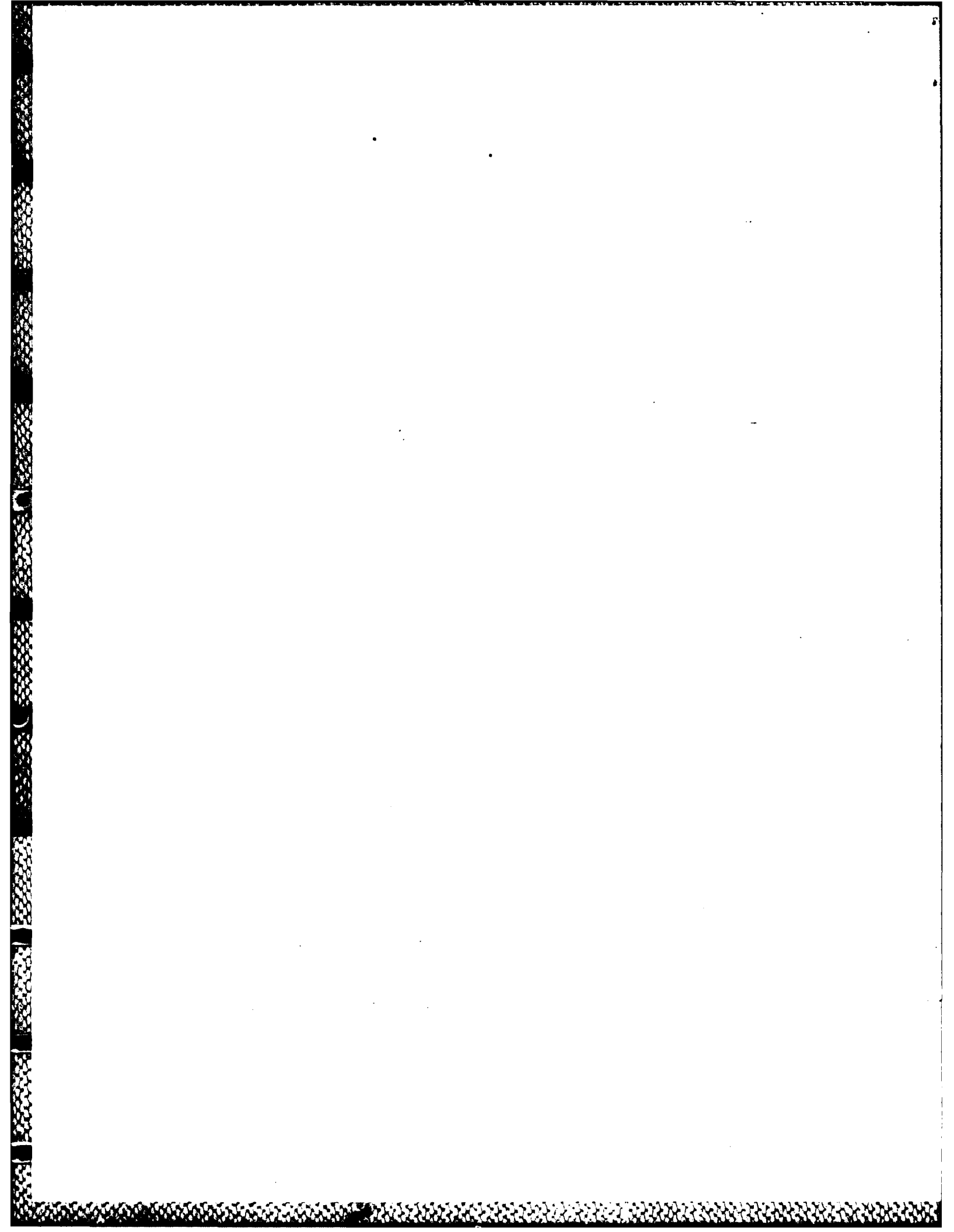
Mr. Greg Logan, Defense Technical Information Center  
Mr. Don Stewart, Defense Technical Information Center  
Mr. Larry Jenkins, Defense Technical Information Center  
Mr. Carl Malm, Jr., Defense Technical Information Center  
Mr. Mike Worth, Defense Technical Information Center  
Mr. James Erwin, Defense Technical Information Center  
Mr. Ernest Rhoad, Defense Technical Information Center  
Mr. Richard Astrayka, Defense Technical Information Center  
Mr. Robert Besson, Defense Technical Information Center  
Mr. Herman Frederick, Defense Technical Information Center  
Mr. Clifford Smith, Defense Technical Information Center  
Ms. Sylvia Sewell and Staff, Defense Technical Information Center  
Mr. Dennis Dunn, Defense Technical Information Center  
Mr. Al Rosati, Defense Technical Information Center  
Mr. Jim Douglass, Defense Technical Information Center  
Mr. John Freeman, Defense Technical Information Center  
Ms. Brenda Smith, Defense Technical Information Center

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## Executive Summary

One of the primary missions of DLA is to provide supplies for hundreds of thousands of lines of inventory to customers in the Military Services, other Federal Agencies, and friendly foreign governments. Among those supplies is food or subsistence supplies. Paramount to the proper execution of the supply mission is the decision of when and how much to buy for replenishment of the DLA inventory in anticipation of customer demand. The validity of that decision depends on the Agency's ability to forecast customer demand.

Forecasting can either be qualitative or quantitative. Quantitative forecasting is the subject of this report. The techniques of quantitative forecasting begin with past data values and, following a systematic procedure, develop a prediction of future data values. The Defense Logistics Agency (DLA) uses quantitative forecasting to predict customer demand.

In 1980, DLA embarked on an effort to improve demand forecasting for the Subsistence commodity. This study concludes the analysis portion of that effort. The objective of the study was to investigate techniques for improving demand forecasts over lead times and procurement cycles.

In inventory management, the lead time is the length of time between the decision to replenish the item and the actual addition of its order quantity to the inventory. The procurement cycle is the length of time between successive buys. Safety levels represent extra inventory held as buffers against errors in demand and lead time forecasts. Demand forecasting links actual customer requirements and ordering habits (outside DLA's control) to these inventory levels held in anticipation of customer demand (within DLA's control).

Consequently, DLA's ability to accurately forecast demand or sales directly impacts on its mission performance. Specifically, improved forecasting will result in the following:

- o Improved customer service by enhancing management's ability to order the proper quantity of the right items at the right time.
- o Reduced safety stocks required to meet customer requirements. (DLA presently maintains safety stocks of \$95 million (end FY 84) for Subsistence.)
- o Reduced risk of acquiring items in "long supply," less waste, merchandising stock at less than cost and other associated inventory costs.

On the other hand, inadequate forecasting results in the following:

- o Increased management effort required to meet customer requirements.
- o Increased operational costs due to spot buying and higher stock levels.
- o Increased risks of acquiring long supplies of materiel and the subsequent resource expenditures needed to manage the materiel.

Presently, DLA does not have perfect information on the factors that drive customer demands. Wide swings in demand due to special customer requirements can not be predicted by quantitative forecasting. However, quantitative



forecasting can be employed to minimize the variation between forecasted and actual demands of a recurring nature.

As stated before, the purpose of this study was to evaluate and test quantitative forecasting techniques to better plan for the replenishment of inventories for the Subsistence commodity. A primary reason for the initiation of the study is the existence of seasonal demand patterns in the subsistence commodity. Seasonal patterns occur when demand fluctuates in a similar way within a certain period (annually, quarterly, etc). Seasonality is not considered under present subsistence forecasting methods. About 1 out of 7 subsistence lead time demand series exhibit a seasonal pattern.

The approach to this study involved the following steps:

- Structuring historical demand data for the purpose of forecasting.
- Fitting various forecasting models based on 1978-1979 demand data.
- Evaluating those models based on the forecasted vs. actual demand for 1980 - 1983 demand data.
- Selecting the best individual model and or group of models for possible implementation.
- Testing methods to track forecast errors so that the models can be switched within the group. This is necessary when the assigned model no longer is tracking the demand pattern.

Analytical efforts of this study involved processing 7,850 subsistence demand series through more than 100 forecasting models. Complete documentation and explanation of tested forecasted models are included in the main study report.

The key findings of this study are as follows:

- Over the 1980 - 1983 time frame, the standard deviation of lead time demand derived from the current DLA forecast model was 20% larger than the standard deviation of lead time demand derived from a group of five alternative models.
- The group of five models includes two seasonal models which would provide the capability to forecast seasonal demands within the subsistence commodity.
- A new tracking signal was identified which responds more effectively to demand variation and provides the criterion for forecast model selection within the group.
- The recommended model group can be implemented as the Demand Forecasting Module for Management Requirements Determination under the new Defense Integrated Subsistence Management System (DISMS). The Demand Forecasting Module provides DISMS with the capability to develop, evaluate, compare, and control demand forecasts for the subsistence commodity.

Based on these findings, the Executive Director for the Directorate of Supply Operations should develop an implementation plan to incorporate the prototype forecasting system in this report into a Forecasting System Module for Management Requirements Determination under DISMS. The implementation costs are small when considered against the benefits gained. Specifically, these benefits include:

- Less safety stock to meet customer requirements.
- Reduced need for "crisis" management due to stockouts.
- Improved customer satisfaction.
- Less merchandizing of short shelf-life materiel.

In summary, DLA relies on customer requirements to schedule the timing and quantity of buys. For the subsistence commodity, seasonal patterns occur in 14% of item lead time demand distributions. Significant reductions in subsistence demand variation can be achieved through the replacement of present subsistence forecasting methods. The recommended model group can be expected to provide around 20% better lead time demand forecasts than existing methods. Moreover, the recommended tracking signal will provide more responsive warnings to management when demand patterns change. The application of quantitative forecasting techniques to the subsistence commodity, while not a panacea, can significantly improve the inventory management of that commodity. The implementation of these techniques in a Forecasting System Module serves as a major step toward the future in the development of the new Subsistence Requirements Determination System.

## I. INTRODUCTION

### A. Background

1. What is Forecasting. Forecasting is the prediction or estimation of future events and is an invaluable component of business planning. Effective planning sets goals and objectives for an organization and the strategies to attain these goals. Forecasting provides the benchmarks by which plans and policies can be developed to respond to future opportunities and problems. In business, better forecasts are needed since decisions usually involve dollars and the successful performance of a mission.

2. Specific Tasking. One of the primary missions of DLA is to provide supplies for hundreds of thousands of lines of inventory to customers in the Military Services, other Federal Agencies, and friendly foreign governments. Among those supplies is food or subsistence supplies. Paramount to the proper execution of the supply mission is the decision of when and how much to buy for replenishment of the DLA inventory in anticipation of customer demand. The validity of that decision depends on the Agency's ability to forecast customer demand.

Forecasting can either be qualitative or quantitative. The selection of a qualitative or quantitative technique depends on the specific application as well as on the information available to formulate a forecast.

Qualitative forecasting is best suited to those situations in which historical data is not readily available or applicable and in which judgement must be heavily relied upon. It is used to forecast changes in processes which may be the result of exogenous influences. Qualitative techniques are often applied only to long term situations due to their dependence on expert judgement and subjectivity.

Quantitative forecasting is the subject of this report. The techniques of quantitative forecasting begin with past data values and, following a systematic procedure, develop a prediction of future data values. With the onset of computers, application of quantitative forecasting has become widespread. Quantitative techniques have a track record of better accuracy and lower cost, and are generally accepted over qualitative techniques. Many quantitative techniques have been developed and applied by Government and industry to uncover the basic patterns of historical data in order to develop forecasts. Monitoring methods which send a signal to management when these patterns change are critical to the application of quantitative forecasting.

In 1980, the DLA Operations Research and Economic Analysis Office (DLA-LO) was tasked to discover what forecasting techniques should be applied for subsistence items. As a substantial number of subsistence items possess seasonal demand patterns, various forecasting methods not presently used by DLA had to be investigated. An objective of the tasking was to identify those item/demand characteristics that result in the assignment of a specific forecasting technique for established items. Based on this assignment, decision rules for assigning forecasting techniques to new items could be established. After initial review of the problem, the Defense Logistics Agency (DLA) contracted with Inductive Inference, Incorporated, to identify and test new techniques for a small sample of subsistence items. The test was successful and a report documenting the results was provided in October 1982 (Reference 13).

The DLA is currently implementing a plan for the worldwide integrated management of wholesale subsistence stocks. The Defense Personnel Support Center (DPSC), a primary level field activity of DLA, is the inventory control point for the subsistence commodity. The Defense Integrated Subsistence Management System (DISMS) encompasses all automated information systems that support subsistence management. As such, the design quality and integration of DISMS is critical for the success of this plan. Moreover, demand forecasting is a primary component in the management requirements determination process under DISMS.

In March 1983, the DISMS task group delivered the final Management Requirement for Forecasting which included the results of the contracted test. The DISMS Management Requirement for Forecasting demonstrated that better forecasting can be achieved through the decomposition of demand patterns into trend, seasonal, and random components. Also it was found that forecasting the lead time demand was better than developing a forecast based on a monthly forecast spread over the lead time.

DLA awarded a second contract to Inductive Inference, Incorporated in late 1983 to extend the techniques used in the first contract to the entire subsistence commodity and to identify patterns in item/demand/model assignment.

Due to the large volume of work involved and limited contract funding, DLA-LO employed a team approach with the contractor and DISMS task group and extensive support staff.

B. Statement of Problem. The demand forecasting techniques presently used by DPSC attempt to accurately track the underlying demand patterns for subsistence items. However, numerous statistical factors and policy influences exist that affect there patterns and complicate tracking. They are as follows:

1. Policy Influences - Created by management to enhance customer support or reduce cost, they include such actions as spot buys, promotional sales, item substitution, etc.
2. Statistical Factors -
  - a. Average Level - The underlying horizontal demand pattern which does not tend to increase or decrease in a systematic way.
  - b. Trend - The rate of growth or reduction in the average level of demand that is occurring from period to period.
  - c. Seasonality - Generally, recurring patterns at certain interval as a consequence of time of year. Examples are holiday items, ice cream, spareribs, cocoa, etc.
  - d. Cycle - Long-term (3-10 years) factors generally affecting the entire economy, heavily influenced by Government decisions and world politics.
  - e. Randomness - Represents all influences not included in level, trend, seasonality, and cycles. Includes such things as sampling error, acts of God, etc.

The problem is to identify forecasting methods which more accurately track

demand in light of these policy influences and statistical factors.

### C. Objectives

The objectives of this study are:

1. To develop a prototype forecasting system to test and evaluate a variety of forecasting methods for the subsistence commodity.
2. To develop a set of decision rules to assign forecasting methods to new items in the subsistence inventory.

### D. Scope

1. Project Effort. This study addresses a large scale test and evaluation of quantitative techniques for forecasting item/warehouse demands within the subsistence commodity. New techniques were identified that significantly reduce the forecast error and bias encountered with presently used methods. It is the intent of the authors that the methodology, findings, and conclusion of this study provide a first step towards the implementation of improved forecasting in DLA automated materiel management systems.

The study was limited in the following manner:

1. Monthly demand for stocked items at each subsistence wholesale depot for the period July 1977 - November 1983 (77 months) were extracted from the Defense Personnel Support Center (DPSC) files.
2. Each stocked item experiencing 48 months of nonzero demand for the period September 1979 - August 1983 was screened for further analysis (3,925 item/warehouse records).
3. Existing software developed under the previous contract study with Inductive Inference, Incorporated, was upgraded to increase its flexibility and power.
4. To provide management with information to assist in the decision of when and how much to buy, lead time demand forecasts and demand forecasts for the procurement cycle following the lead time were generated. No aggregation above the item/depot level was made.
5. Software was developed to augment forecast model identifications and estimations, to test model assignments to classes of items, and to evaluate forecast adequacy across the entire class of models. A group of models were recommended for final analysis and implementation.

An assumption of the study was that one hundred percent (100%) of nonrecurring demand for perishable items was included with recurring demand for forecasting at the wholesale level.

2. Report Organization The two volumes of this report document the work performed by the study team. Volume I, the Study Report, presents a general review of the study assignment, methodology, analysis, findings, and recommendations. Volume II addresses specific details about forecast model assignments for the subsistence commodity and the description of model formulas.

Section II of Volume I describes the current Subsistence commodity. The reader who has a general knowledge of the management subsistence may wish to bypass Part A, An Overview, and go directly to Part B; Demand Forecasting. The reader who has a comprehensive knowledge of subsistence and the role of demand forecasting may elect to skip Section II in its entirety.

## II. THE SUBSISTENCE COMMODITY

### A. An Overview

The availability of wholesome and popular food and foodstuffs (known as subsistence) both on the mess hall table and on the commissary shelf is critical to the health and morale of the U.S. Forces and their families. DLA has the mission to provide high quality subsistence to the Military Services, some Federal agencies, and authorized foreign governments.

#### 1. Subsistence Categories

The subsistence commodity management is presently split into two categories: perishable and semiperishable. Perishable subsistence includes nonstocked items such as fresh fruits and vegetables, bread and milk and stocked items that require chilling or freezing. Semiperishable subsistence includes items that do not require chilling or freezing such as canned goods. Within the categories of perishable and semiperishable subsistence, items are classified as (1) troop issue - those generally intended for troop feeding and, to a minor extent, for commissary resale; and (2) brand name, those generally intended for commissary resale and, to a minor extent, for troop feeding. Brand name items are characterized by an alphabetic character in the seventh digit of the stock number.

Table 1 shows the primary federal supply classes (FSCs) that are managed under the subsistence commodity. Table 1 does not contain the FSCs for minor super-market brand name semiperishable items, similar to convenience store items, such as flyswatters, brooms, light bulbs, etc. However, these items are stocked in the supply system and are included in this study.

The great majority of subsistence items occur in the following federal supply classes (FSCs):

Table 1

FEDERAL SUPPLY CLASSES FOR SUBSISTENCE

| <u>FSC</u> | <u>Title</u>   |
|------------|--|
| 8905       | Meat, Poultry, and Fish                                  |
| 8910       | Dairy Foods and Eggs                                     |
| 8915       | Fruits and Vegetables                                    |
| 8920       | Bakery and Cereal Products                               |
| 8925       | Sugar, Confectionary and Nuts                            |
| 8930       | Jams, Jellies and Preserves                              |
| 8935       | Soups and Bouillons                                      |
| 8940       | Special Dietary Foods and Food<br>Specialty Preparations |
| 8945       | Foods, Oils and Fats                                     |
| 8950       | Condiments and Related Products                          |
| 8955       | Coffee, Tea and Cocoa                                    |
| 8960       | Beverages, Nonalcoholic                                  |
| 8965       | Beverages, Alcoholic                                     |
| 8970       | Composite Food Packages                                  |
| 8975       | Tobacco Products   |

2. Mission

The mission of subsistence commodity management within DLA is executed by DPSC's Subsistence Directorate (DPSC-S) through Subsistence Field Activities in CONUS and overseas, with support from certain Defense Depots, Military Service Activities, and Worldwide Integrated Management of Wholesale Subsistence Stock (WIMS) agents.

The customers for subsistence are mess halls and other base installations, and commissaries from which the items are resold to authorized buyers.

3. Special Characteristics. Some characteristics of the subsistence commodity which, in total, make it different from other commodities managed by DLA, are as follows:

a. Shelf Life Limitations. Useful life may be short and is variable; affected by handling and distribution.

b. Storage and Transportation. Refrigeration is required for many items; humidity must be controlled; piling is limited as is product mixing; high transportation per unit costs.

c. Product Utilization. "Fill or kill" requisition policy; low unit costs; high morale factor.

d. Product Availability. Depot shipment vs. direct vendor delivery vs. local purchase; seasonality of demand.

For morale and health purposes, it is necessary to provide a wide variety of subsistence products to the customer on demand.

#### 4. Automated Materiel Management Systems

The DPSC uses three different automated systems to assist managers in providing logistics support to customers throughout the world. The Perishable Subsistence Automated Supply System (PSASS) is used to compute requirements, buy actions, and safety levels for perishable troop issue and brand name items overseas and perishable troop issue items in CONUS.

The Semiperishable Central Stocked System computes requirements, buy actions, and safety levels for semiperishable troop issue and brand name items overseas and semiperishable troop issue in CONUS.

The Direct Commissary Support System (DICOMSS) is used to provide direct supply support services for brand name items and items restricted to large commissary customers overseas but not supplied in CONUS. Within PSASS and the Central System, demand forecasts are generated which drive the timing and quantity of buys. Residual Stocks from DICOMSS shipments are held in the depots for future issue.

Further detail and illustrations on these management systems and subsistence requisition processing are provided in Appendix A.

#### B. Demand Forecasting

##### 1. Demand Accumulation

DPSC stocks certain classes of items at the various depots to account for inaccuracy in demand forecasting, delayed contract deliveries, etc. Customer demands are supported either from storage or by direct vendor delivery. Demands which are less than a carlot are supported from depot stock and are used to generate forecasts. Customer demands that can be met with carlot shipments are supported by direct vendor delivery and are not used in demand forecasting.

In the semiperishable item Central Stock System, both recurring and 100 percent of nonrecurring demand are used in demand forecasting. In PSASS, only recurring demand is used. When a customer submits a recurring requisition for an item out of stock, the requisition is killed but the demand is stored. The demand forecasts used to develop stockage levels at the various depots are the subject of this section of the report.

2. Demand Forecast Computations. Monthly demand forecasts are computed for each location/type pack, as follows:

a. For both perishable chill and freeze items overseas and selected CONUS items, a three-month weighted average is calculated by adding two-thirds of the current month's demand to one-sixth of each of the past two months' demands. This is equivalent to a simple 4-1-1 moving average (known as the D-forecast).



Officially, for CONUS locations, purchases are made only for open funded requisitions for the past and current months (R-forecast) on the requisition status file. However, because other requisitions with short lead times may be received after the purchase is initiated, the 4-1-1 forecast is also applied for CONUS purchases and for safety level computations. General lack of confidence in both of these methods has led to item managers examining recent trends and this month's demand at the same time last year to estimate lead time demand, especially for brand name items.

b. Semiperishable subsistence is forecasted using single exponential smoothing with trend correction (modified double exponential smoothing). (See Appendix A for further discussion of the exponential smoothing techniques.) A general formulation for this method is:

$$\text{The forecast } y_{t+m} = b_0 + b_1$$

$$\text{where: } b_0 = 2S'_t - S''_t$$

$$b_1 = (S'_t - S''_t)/(1 - \alpha)$$

$$S'_t = \alpha d_t + (1 - \alpha) S'_{t-1}$$

$$S''_t = \alpha S'_{t-1} + (1 - \alpha) S''_{t-1}$$

$$d_t = \text{demand for time period } t$$

$$m = \text{number of periods ahead to be forecast}$$

$$\alpha = \text{weighting factor}$$

Forecasts are computed for three alphas: .10, .15, and .20. For each forecast, the absolute deviation is computed as the absolute value of the difference between the last month's demand and the forecast of the last month's demand. The single exponential smoothed average of successive absolute deviations is designated as the mean absolute deviation (MAD). The alpha forecast, which yields the lowest MAD, is chosen to forecast future demand. Note that the DLA forecast is constant over all future periods.

c. Perishable fresh fruits and vegetables (FF&V) are forecast by the individual Defense Supply Offices (DSOs). Carlottable hardy FF&V are forecast using the demand for the same month a year earlier as adjusted by considering intangibles such as climatic conditions, fair market value, and increases or decreases in the number of personnel support. These forecasts are largely and necessarily subjective since such intangibles make a mechanical forecast impracticable. All other FF&V are purchased daily by field buyers to satisfy customer requirements received by telephone.

d. Item managers may override the mechanical forecasts for both perishable and semiperishable subsistence.

Table 2 summarizes the current demand forecast techniques for subsistence items and safety level computations.

Table 2

Demand Forecast Methods and  
Safety Level Computations for Subsistence

|                              | Demand Forecast  | Safety Level  |
|------------------------------|--|---|
| PERISHABLE                   |  |   |
| Overseas                     | $D\text{-Forecast} = \frac{4 D_t + D_{t-1} + D_{t-2}}{6}$ $D_t = \text{last month's demand}$ | $\frac{1}{2} D - \text{Forecast}$ <p>(15 days stock)</p>  |
| COMUS (Troop Issue Items)    | Open funded requisitions (current and past month)  | $\frac{1}{2} D - \text{Forecast}$ <p>(15 days stock)</p>  |
| Exceptions (Some Brand Name) | D-Forecast = this period's demand last year (modified for recent trend)                      | $\frac{1}{2} D - \text{Forecast}$ <p>(15 days stock)</p>  |
| SEMI PERISHABLE              |  | Can be fixed at 0, 1/2, 1, 1-1/2 times the monthly forecast.  |
| Overseas Troop Issue         | Double Exponential Smoothing, $\alpha = .10$ , .15, or .20; Giving Least MAD                 | Can be variable; Service Level Function by NSN/Warehouse<br>$.5F < VSL < 1.5F$                                      |
| Brand Name                   | Double Exponential Smoothing, $\alpha = .20$   | at Oakland (NDS),<br>= MAX (VSL, 2 x FILL QTY) <sup>1</sup>   |
| COMUS Troop Issue            | Double Exponential Smoothing, $\alpha = .10$ , .15, or .20; Giving Least MAD                 | at Norfolk (NNS),<br>= MAX (VSL, 3 x FILL QTY) <sup>1</sup>   |
|                              |  | at San Diego (NDS), Pearl Harbor (NPS), Charleston (NRS),<br>= MAX (VSL, highest one month demand in last 6 months) |

<sup>1</sup> FILL quantity refers to the Fleet Issue Load List stocked for Navy customers.

### 3. Unique Characteristics of Subsistence that Affect the Forecast

Subsistence item demands are independent in the sense that the demands are not driven by demand for "higher level" end items as are the demands for many hardware items. Subsistence demands tend to be continuous rather than lumpy. Subsistence item lead times and procurement cycles are short, averaging 4.5 and 1.5 months, respectively. The independence and continuity of subsistence demands and relatively short replenishment cycles improve the chances that quantitative forecasting methods can be applied to the commodity with success.

Finally, In subsistence inventory management, back orders are not filled. Therefore future demand is not dependent on past supply performance.

### 4. Use of the Demand Forecast

The demand forecast is used in subsistence inventory control systems to calculate procurement cycle demand, lead time demand, and safety levels. The sum of the lead time demand forecast and the safety level combine to make the reorder point which determines when to initiate a replenishment buy action. Presently, the procurement cycle and lead time demand are computed as the monthly demand forecast times the number of months in the procurement cycle period and lead time, respectively. The safety level computation is more complex (see Appendix I). Item managers frequently override the present machine-generated forecasts with their own calculations for seasonal and brand name items.

Safety stocks are needed to cover demand during the lead time when the actual demand exceeds the forecasted demand, the actual lead time exceeds the forecasted lead time or both. In subsistence inventory control, lead times are considered relatively constant and the emphasis is on the variation of demand over the replenishment cycle. If the actual demand exceeds the forecasted demand and safety level, then the customer will receive a substitute item or nothing at all. If the actual demand is less than the forecasted demand then inventory levels rise, increasing long supply, disposals and the merchandising of items at less than cost.

C. Description of the Demand Data Base. The present automated supply system for perishable subsistence maintains an on-line data store of twelve months of demand history while twenty-four months of history is held for semiperishable subsistence. Offline data stores of monthly demand history back to July 1977 are available for both categories of subsistence items. For this study, each item/ warehouse demand record with 48 months of nonzero demand beginning November 1979 for perishable items and September 1979 for semiperishable items was extracted and analyzed. The existing off-line DPSC demand data base which contains records from 1977 to 1981 did not record type pack information. Therefore, the demands were aggregated by type pack for each stock number by warehouse. The record layout is provided in Appendix C. A description of the record fields for each SN/warehouse location is provided in Table 3.

Table 3

ITEM/WAREHOUSE DEMAND RECORD FIELDS

| <u>Field</u>             | <u>Description</u>  |
|--------------------------|---|
| SN                       | Stock Number (Brand Name - 7th character is alphabetic)                                     |
| Type Pack                | Domestic Pack = 1, Export Pack = 2 (Semiperishable only)                                    |
| Depot Code               | Three characters = semiperishable, two characters = perishables (See Tables 2 and 3)        |
| Issue Code               | Troop Issue = 1, Commissary Resale = 2  |
| Supply Code              | Item Supplied from Warehouse = 1, Item Supplied from Direct Vendor Delivery = 2             |
| Item Number              | Five digit code used as identification in lieu of SN  |
| Procurement Cycle Period | Days between successive procurements  |
| Lead time                | Days between initiation of a buy action and receipt of the product at the depot             |
| Fleet Code               | Norfolk or Oakland = 1, Otherwise = 0 (Semiperishable only)                                 |
| Chill Code               | Chill = 1, Freeze = 2, Semiperishable = 9   |
| Shelf Life               | The period of time after production of an item during which it must be utilized             |
| Safety Level Code        | If VSL, code = 0<br>Fixed at 0 mos = 1<br>at 1-1/2 mos = 2<br>at 1 mos = 3<br>at 1/2 mo = 4 |
| Unit of Issue            | Designates the manner by which an item is issued such as jars, cans, bags, lbs.             |
| Average Net Weight       | Weight of product excluding packaging   |
| Nomenclature             | Short description of item   |

Perishable Only

|                         |  |
|-------------------------|--|
| Recurring Demand Qty    | From the customer's perspective, those demands that are regular in frequency   |
| Nonrecurring Demand Qty | From the customer's perspective, those demands that are irregular in frequency |

Table 3 (Continued)

Semiperishable Only

|                          |   |
|--------------------------|---|
| Troop Issue Demand       | Demand supplied for troop feeding   |
| Commissary Resale Demand | Demands supplied for resale in Military commissaries. The items demanded may be troop issue items as well as brand name |

For this study, the demand were captured monthly from July 1977 through November 1983.

III. DEMAND FORECASTING METHODOLOGY AND ANALYSIS

A. An Overview. This section of the report describes the general philosophy and the methodology used to apply quantitative demand forecasting techniques to the Subsistence Commodity. Details are left to the appendices in Volume I and Volume II. Figure 1 provides an overview of the Demand Forecasting Methodology. There are six components to the methodology, as follows:

1. Forecasting System Design Considerations - This area describes the general environment and technical problems which must be surmounted in the design of the subsistence demand forecasting system.

2. Data Acquisition and Structuring - Data acquisition involves the determination of the number of demand observations and item characteristics needed to analyze subsistence demand patterns. In this study over 70 observations were available for most items/warehouse demand series so that it was feasible to identify and evaluate the underlying demand patterns. Data structuring involves the aggregation of monthly demands into lead time and procurement cycle sums and the notation used to predict future demands based on past demands over a predictor period. This predictor period may be the last month, last lead time or procurement cycle or any other specified period.

3. Forecasting Techniques - This area provides details on the identification and fitting of a wide range of quantitative forecasting methods to subsistence demand series.

4. Evaluation Criteria - This area describes the various statistical evaluation criteria used to rank the competing models.

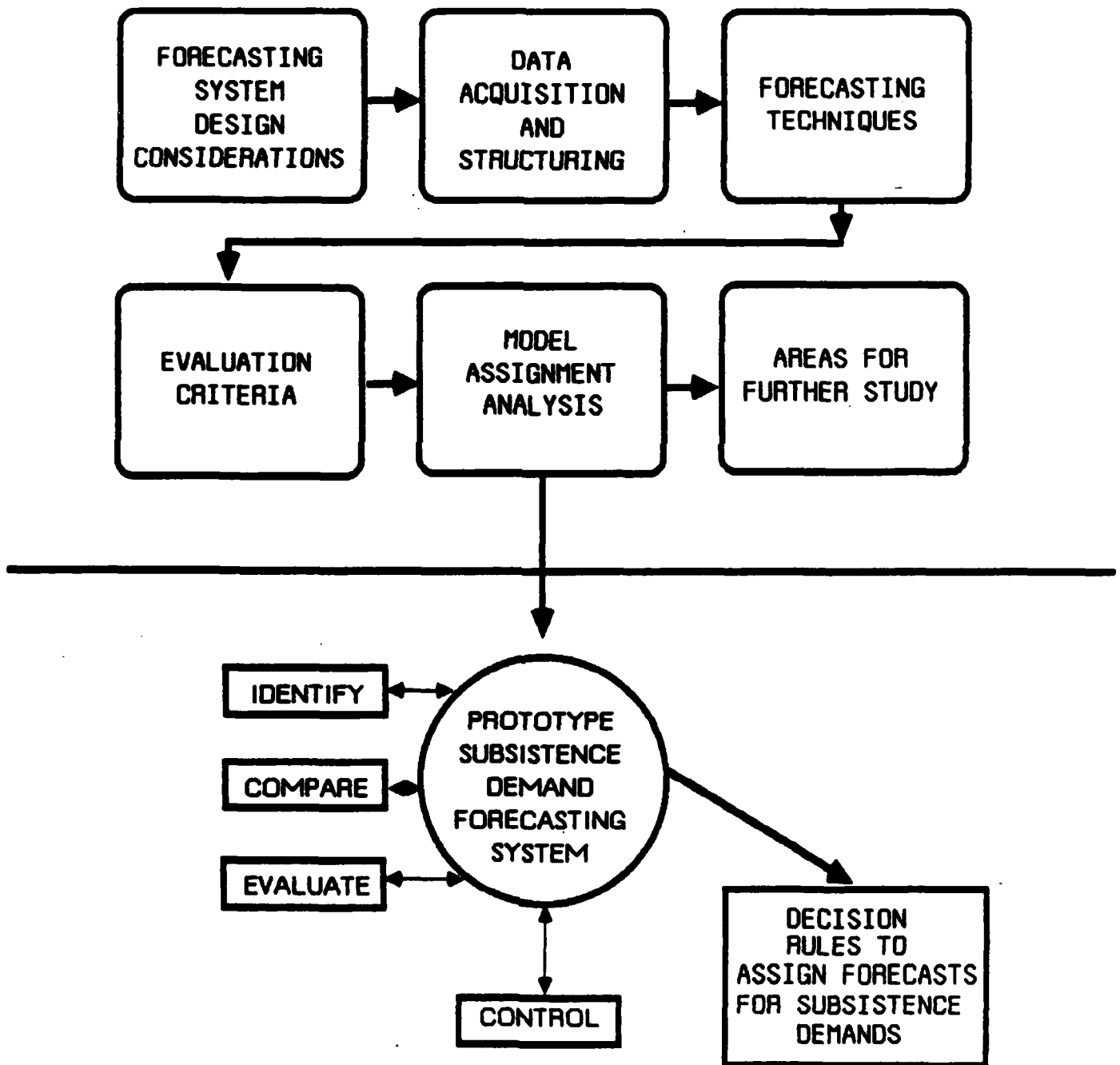
5. Model Assignment Analysis - This area involves the assignment of the best individual model and construction of the best group of forecasting methods for the subsistence commodity.

6. Areas for Further Study - This area involves suggestions for further study including adjusting forecasts based on the nature of the forecast error and monitoring forecast performance.

In the remainder of Section III, these components are described in more detail.

FIGURE 1

OVERVIEW OF DEMAND FORECASTING  
METHODOLOGY AND ANALYSIS



## B. Forecasting System Design Considerations

1. Requirements and Technical Difficulties. In designing a forecasting system for Subsistence, the following requirements and technical problems need be considered:

a. Need for Extended Forecasts. Common practice in inventory control is to forecast one period ahead, a month or quarter, and then to develop forecasts by multiplying the forecast by the number of periods in each lead time. However, this approach ignores any seasonality or trends in demand over the lead time. A better approach would be to forecast demand lead time and procurement cycle directly.

b. Need to Handle Large Numbers of Forecasts. Due to the special characteristics described in Section II, subsistence is managed by location; and accordingly forecasts are by item and location. Demand patterns for an item do vary by location, thereby necessitating separate forecasts for each location. There are approximately 40 locations and 4,000 items for a possible total of 160,000 forecasts. The actual number will be less since not every item is stocked at every location. However, since the number of required forecasts is large, techniques which cannot be automated are impractical.

c. Need to Limit Number of Forecasting Techniques. Due to the volume of forecasts, it is not practical to fit individual techniques to each item for each location. The preferred approach would be to find a point of diminishing returns where an increase in the number of techniques would not significantly improve forecast accuracy. Therefore, the number of techniques needs to be limited to the number that will not overload the automated system but still achieve significant improvements in forecast accuracy.

d. Bias in Selecting Techniques. Time series data is generally modeled by using the data both to identify the model (i.e., to determine its form) and to estimate its parameters. A series of models is selected (often by a stepwise procedure) and the parameters of these models are estimated in the data. The model that best fits the data (i.e., with the smallest error) is selected. Such a procedure produces a favorable bias in the error estimate that increases with the number of models considered. "Cross-validation" methods, where a portion of the series is withheld for evaluating the error, would produce no such bias. Such methods however are rarely used when the time series are not long, both because recent data is too important not to be used in model development and because of the extraordinary amount of computation that is require to systematically refit and test portions of the time series. Instead "Bayesian methods" that utilize a distribution of prior probabilities over the set of candidate models are sometimes used to obtain error estimates. More often, a model developed by the analysis of a relatively short time series is evaluated by using all points of a time series, first to estimate its parameters and second, to evaluate its forecasting errors (Reference 5).

e. Spurious Fits. The problems of bias described above are often manageable by the aforementioned techniques when a single time series is being fit. Here, however, a fundamental problem exists; models must be developed for many thousands of time series whose relation to one another is unknown. A model selected for a single time series may spuriously fit that series well. A number of the models so selected for many time series will almost certainly be spurious. Cross-validation of each individual model helps little--many models will most likely spuriously survive cross-validation. Even were such problems manageable, the use of conventional methods to develop models for so many series would be prohibitively cumbersome, time-consuming, and expensive.

f. Piggy-Backing Error. Another difficulty in using conventional methods to develop models that forecast the demands for subsistence items is that their computer realizations are designed for use in developing models that forecast the next point in a time series (i.e., next month's demand). When demand over a longer period is required, a technique called "piggy-backing" is used. Here the forecast point is treated as the last known data point and the next point is forecast. This is repeated until the required future time span has been forecast. This procedure unfortunately produces an error that rapidly increases with each repetition. Forecasts produced in this manner are generally useful only in forecasting the near future. In subsistence, the sum of the demands over a procurement cycle following a lead time (as well as the demand over the lead time) must be forecast for each item. Forecasts from two months to almost a year into the future are often required.

## 2. Approach Taken to Resolve Problems

a. Collection Versus Single Series Testing. A large number of models were tested against each demand series, those that fit these data best were identified (but not selected). However, recognizing that the performance of these models may be spurious, we selected models according to their performance on a collection of demand series rather than a single series. Each such collection will be defined in terms of characteristics of the items and their demand series. A single model will be used to forecast all demand series in each collection. The definitions of the collections will be developed by an analysis that assumes that a sufficient number of series are in each collection so as to maximize the precision of their corresponding models.

b. Division of Series for Development and Validation. Prior to the formation of the collections, those models that best fit each demand series were determined. A validation technique was used to estimate the forecasting error produced by each model. This estimate is not favorably biased. First, the initial 24 to 30 months of the time series (depending upon its length) were used to determine the parameters of the model. The following requisite demand (over lead time or procurement cycle) was then forecast and compared with the actual demand. Thereafter, for each point of the demand series, the parameters were evaluated using only the demands to that point, and a forecast was made and compared to the actual demand. This technique, produces a slightly unfavorably biased estimate of forecast error because only a portion of the series is used at each error evaluation.



c. Reorientation of Independent Variables. Rather than applying a "piggy-backing" technique for generating forecasts, the models used directly forecast either the sum of the demand over the lead time or the sum of the demand over the procurement cycle following the lead time (different models were used for each). That is, the dependent variables were such sums of demands and the independent variables were the monthly demands or a sum of demands over a specified predictor period. The least squares fits were performed using proprietary software in conjunction with a technique for algebraically operating on the demand series to automatically construct the requisite matrices. The software has proved sufficiently economical in computer usage so that it has been, thus far, possible to set the parameters of over 100 models approximately 36 times (i.e., 1 for each of 36 time periods) for both the lead time and procurement cycle forecasts for each of 3,925 item/warehouse demand series. This number of tests was used to estimate the errors produced by each model on each demand series.

C. Data Acquisition and Structuring. The central theme of quantitative forecasting is the assumption that some pattern exists in what has gone before and that the pattern will continue. Each forecasting technique makes explicit assumptions about the type of underlying pattern. The ability of a given technique to forecast effectively in a specific situation depends largely on the characteristics of the pattern. There are five types of basic patterns usually identified as follows:

1. Level is defined as the average of the demand values over a specific period of time.
2. Trend is defined as the growth or decline occurring in demand values over time.
3. Seasonality is defined as regular movements of demand at fixed time intervals apart. The length of the fixed time interval is known as the period of the movement. Periods of 12 months may exist for ice cream, spare ribs, strawberries, etc.
4. Cycles are usually due to long term business activity and are not addressed in this study since the predictive periods for the subsistence items are relatively short.
5. Randomness represents sporadic, short-lived movements in demand due to chance events. Randomness is reflected in the residual left after a demand series has been removed of level, trend, and seasonality.

The purpose of these statistical forecasting methods is to identify and track the level, trend, seasonal, and random components of the demand patterns. In the analyses in this report, each class of forecasting techniques is evaluated as to their appropriateness to identify and track these components.

Data requirements for statistical forecasting vary depending on the technique chosen. In this study, at least 24 lead time demand observations were used to fit the respective technique. The technique was then evaluated for accuracy over the next 24 to 40 months against the current subsistence forecast method.

Table 4 depicts the notation and data structuring used to generate and evaluate demand forecasting techniques for the subsistence commodity.

Table 4

DATA STRUCTURING FOR SUBSISTENCE DEMAND FORECASTING

Monthly  
Demands

|                 |   |     |
|-----------------|---|-----|
| Jan             |   | Nov |
| 80              |   | 83  |
| X <sub>31</sub> | X <sub>32</sub> X <sub>33</sub> ... x <sub>51</sub> X <sub>52</sub> X <sub>53</sub> ... X <sub>61</sub> X <sub>62</sub> X <sub>63</sub> ... X <sub>71</sub> X <sub>72</sub> X <sub>73</sub> X <sub>74</sub> X <sub>75</sub> X <sub>76</sub> X <sub>77</sub> |     |

Let:  $t$  = the last month of observed demand

$LT$  = the lead time (in months) for an item

$PC$  = the procurement cycle (in months) for an item

$X_t$  = the observed demand in month  $t$

$D_{t,R}$  = total demand over  $R$  months including and immediately preceding

$$\text{month } t: D_{t,R} = \sum_{i=1}^R X_{t+i-R}$$

$Y_t = D_{t+LT,LT}$  = the sum of the demands over the lead time following

$$\text{month } t: D_{t+LT,LT} = \sum_{i=1}^{LT} X_{t+i}$$

$Z_t = D_{t+LT+PC,PC}$  = the sum of the demands over the procurement cycle after the lead time following

$$\text{month } t: D_{t+LT+PC,PC} = \sum_{i=1}^{PC} X_{t+LT+i}$$

= the number of "lags" used in autoregressive models--the number of demands including and immediately preceding the current demand that is used in the autoregressive models

$\hat{Y}_t$  = forecast for lead time demand

$\hat{Z}_t$  = forecast for procurement cycle demand.

## 2. Example of Notation Used for Forecasting Techniques

An example of this notation for autoregressive techniques follows.

Let item S be a semiperishable item with a lead time of 4 months and procurement cycle of 2 months. For semiperishable items, 30 months of data were used to initially fit different forecast models.

The notation in Table 4 is applied as follows:

Monthly  
Demands

$X_{25} X_{26} X_{27} \dots x_{30} X_{31} X_{32} X_{32} X_{33} X_{34} X_{35} X_{36} X_{37} \dots$

At  $t = 30$ , the next lead time demand for item S is  $D_{30+4,4} = \bar{D}_{34,4} = X_{31} + X_{32} + X_{33} + X_{34}$ . At  $t = 30$ , the next procurement cycle demand for item S is  $D_{30+4+2,2} = \bar{D}_{36,2} = X_{35} + X_{36}$ . In this example, a forecast will be generated for a simple autoregressive model (without constant) lagged one monthly period. The autoregressive models contain coefficients displaying the portion of past performance which affects or explains future performance. The first 30 months are used to initially fit or "prime" the forecasting models.

The simple autoregressive forecast for the next lead time demand is  $a_1 X_{30}$  where  $a_1$  is determined by the initial fitting. For example, if  $a_1 = 2.62$ ,  $\text{FORECAST}(X_{31} + X_{32} + X_{33} + X_{34}) = 2.62 * X_{30}$ . Similarly, forecast for the next procurement cycle demand is  $b_1 X_{30}$  where  $b_1$  is determined by the initial fitting. If  $b_1 = 1.64$ , then  $\text{FORECAST}(X_{35} + X_{36}) = 1.64 * X_{30}$ . At month 34, the lead time FORECAST, ACTUAL AND ERROR = ACTUAL - FORECAST values are recorded. At month 36, the Procurement Cycle Forecast, Actual and Error = Actual - Forecast Values are recorded. At month 31, the procedure is repeated to develop a  $\text{FORECAST}(X_{32} + X_{33} + X_{34} + X_{35})$  and a  $\text{FORECAST}(X_{36} + X_{37})$ . The autoregressive coefficient is updated also.

The procedure iterates until we forecast  $D_{75,4}$  for lead time demand and  $D_{77,2}$  for procurement cycle demand. The values recorded are altogether recorded for further analysis.

### D. Forecasting Techniques

1. Discussion. In this section, a short description of the classes of forecasting techniques employed in this study is provided. More detail is available in Appendix N. The forecast techniques were selected for a variety of reasons depending on the nature of the underlying demand patterns. In particular, Autoregressive Integrated Moving Average (ARIMA) models were avoided because a monthly update of the parameter estimates is computationally expensive and difficult.

2. Description of Techniques. A short description of each class of forecasting technique is given below. Details are left to Appendix N.

a. Autoregressive Models An autoregressive (AR) model assumes that near item future demands are dependent on past and current demands. The coefficients in the autoregressive model display the fraction of the known demand affecting the future demand. In this study, the autoregressions were limited to lags of 1, 2, or 3 periods past. The study also considered logarithmic and square root auto regressive models (LAR, SAR, AR1, AR2 and AR3).

The AR3 forecasts would be as follows:

$$\begin{aligned} \text{Lead Time Demand Forecast} = & a_1 * (\text{last period's demand}) \\ & + a_2 * (\text{demand two periods ago}) \\ & + a_3 * (\text{demand three periods ago}) \\ & + a_4 \end{aligned}$$

where the parameters,  $a_1$ , are determined by least square fits.

$$\begin{aligned} \text{Procurement Cycle Demand} = & b_1 * (\text{last period's demand}) \\ \text{Forecast} & + b_2 * (\text{demand two periods ago}) \\ & + b_3 * (\text{demand three periods ago}) \\ & + b_4 \end{aligned}$$

where the parameters,  $b_1$ , are determined by least square fits.

We may set  $a_4 = b_4 = 0$  (autoregressive without constant) or we may achieve extra freedom in the model fitting by allowing all real values for  $a_4$  and  $b_4$ .

The inclusion of parameters  $a_4$  and  $b_4$  allows for tracking the average level of demand over the study period so that the autoregressive parameters can model changes in the average demand. This allows for demand series with a relatively constant change in demand to be fit by setting the autoregressive parameters equal to the periodic changes. In fact, a fractional change in demand may be modeled by the autoregressive parameters while the constant terms capture the additive component of change in demand. Some of the benefits of integrated models (to be discussed) may be achieved by these models while integrated techniques can be used to fit varying changes in demand.

b. Autoregressive Models with Harmonic Terms These models (AR1 HARM, etc.) are identical to the autoregressive models above, except for the inclusion of a harmonic term,  $A \cdot \sin \left[ \left( \frac{2\pi}{C} t + \theta \right) \right]$ , which introduces a amplitude change and phase shift at time  $t$  to the fitting of the demand data. In this study only  $C = 12$  for monthly demands was examined.

Note that for computational purposes:

$$A \cdot \sin \left( \frac{2\pi}{C} t + \theta \right) = a' \sin \frac{2\pi t}{C} + a \cos \frac{2\pi t}{C}$$

These models will capture consistent sinusoidal seasonal variations in demand. However, if the seasonal effects are changing from year to year and the variations are not sinusoidal, these models may introduce serious distortions.

c. Autoregressive Models with Lag Seasonal Terms. These models (AR1 LAG, etc) are identical to the autoregressive models with the exception that an additional demand period 12 months prior was included for extra freedom in the autoregressive fitting process. These models have the additional feature over simple autoregressive models of tracking varying seasonal effects that are not sinusoidal. The predictor periods and the lag periods (3, 6, 9, etc.) may be altered based on management concerns. For example, if cheese items exhibit quarterly peaks due to customer buying habits at certain times, these methods can best track the seasonal component and result in better forecasts.

d. Integrated Autoregressive Models. While autoregressive models with a constant can model certain additive trends, integrated autoregressive models (IAR) can best predict demand when the trend component changes stochastically subject to random shocks. These integrated autoregressive models are similar to autoregressive models except that the independent variable is the difference in demand between successive time periods and the dependent variable is the difference between the forecast and this period's demand. A constant may be included in the regression, if necessary.

e. Integrated Autoregressive Models with Harmonic Terms. These models (IAR HARM) are similar to the above except for the addition of the harmonic term. They may be used when the demand pattern exhibits varying trend and relatively constant sinusoidal seasonality.

f. Integrated Autoregressive Models with Lag Seasonal Terms.

These model (IAR LAG) are identical to integrated autoregressive models with the exception of an additional term which is the difference of demand over successive periods 12 months ago. (See Appendix N for the formula.) They may be used to model varying trend and "spiked" seasonal demand patterns.

Longer predictor periods can smooth out random fluctuations in the demand data. For this study, lead time/procurement cycle demand and six month sums of demands were examined.

Integrated (short-term differenced) data are used to stabilize time varying levels while logarithmic and square root transformations are included to stabilize time changing standard deviation and variance of the demand data respectively. Harmonic and lag seasonal models are included across all these classes of models.

g. Averaging Methods

Averaging methods (MO AVG) employed in this study were limited to 3, 6, 9, 12, 15, 18, 21, 24, and 36 months moving average and a arithmetic average or global mean.

The moving average methods generate the next period's forecast by averaging the actual demand over a certain period. These methods are intended to cancel out random fluctuations in demand. The methods do not accommodate seasonality. A wide range of periods was studied to determine the proper length of period.

Too few periods will result in seriously distorted forecasts influenced by random variations in demand. Too many periods will result in lagging forecasts which fail to track trends. When the level of the demand does change, the proper moving average will respond well unlike the last period demand forecast which will fail to adjust at all.

The arithmetic average or global mean is the arithmetic average of all actual demand values from the start to the end of the evaluation period.

The arithmetic average will smooth out random fluctuations, but for long evaluation periods, it does not respond well to trends nor seasonality. It takes little account of recent data. It is appropriate for randomly distributed data with a constant level.

h. Naive Methods. Managers often look to the last period's data or this period's data one year ago before making decisions concerning stock buys and levels. In this report, these techniques are denoted as:

(1) Last Period's Observation. For this method, actual demand is the forecast for the predictor period. The last period's observation may work well with data that exhibit local monotonic trends, but it does not accommodate seasonality and may "chase" random fluctuation resulting in poor forecasts.

(2) This Period Last Year. This technique (LAST YEAR) merely uses the demand recorded for the predictor period one year ago as the predictive period forecast. This method ignores recent observations and therefore fails to track trends. The method is appropriate for demands with an annual seasonal pattern and constant level; however, it can overreact to random fluctuations.

i. Exponential Smoothing (Exponentially Weighted Moving Average). Exponential smoothing techniques are widely used in Government and industry due to their ease of computation and minimal data retention requirements. Single exponential smoothing (SES) and double exponential smoothing (DES) are more commonly used.

The choice of a smoothing constant is critical to the performance of the exponential smoothing methods. The order of exponential smoothing is usually decided by visual inspection of the data. For demand series with slowly changing levels, single exponential smoothing is selected. For demands that grow or decay linearly over time, double exponential smoothing is chosen. Smoothing constants between .05 and .30 are usually suggested. However, in this study, smoothing constants of .4, .5, .6, .7, .8, and .9 were also tested.

There are many methods to adjust exponential smoothing for seasonal patterns. One such famous method is known as Winter's seasonal forecast procedure. Winter's procedure incorporates three smoothing constants; one to update the level, one for trend, and one for seasonality. Because of the effort required to estimate the proper smoothing parameters, the Winter's method was not included in this study.

Extreme care must be taken when describing the formulae and computer code for double exponential smoothing.\* Many erroneous formulae have, in fact, been published and caution is warranted when dealing with the subject. The correct formula for the one period ahead forecast under double exponential smoothing is:

$$(2S^1 - S^2) + \frac{\alpha}{1-\alpha} (S^1 - S^2)$$

where  $S^1$  is the single smoothed average,  $S^2$  is the double smoothed average and  $\alpha$  is the smoothing constant.

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\* See Reference 3; Gardner, E. S., "The Strange Case of the Lagging Forecast," Interfaces, May-June 1984.

As used by DLA, the subsistence semiperishable forecast calculates the double smoothed one period ahead forecast correctly, but then simply multiplies the monthly forecast by the lead time period. Trends are assumed constant over the lead time.

The exponential smoothing parameters,  $\alpha$ , in the single and double exponential smoothing formulae above, are constant.

Another technique known as Adaptive Response Rate Single Exponential Smoothing (ARRS( $\gamma$ )) allows for the controlled change of the smoothing parameter. At each period, the absolute value of the single smoothed average error and the single smoothed average absolute error through the last period is calculated. The new smoothing constant is chosen as the minimum of this ratio and  $\gamma$ . The constraint method was needed due to wild forecast fluctuations when the smoothing was unconstrained. COMBINED exponential smoothing is discussed in Section IIIE.

3. Model Identification. Figure 2 provides a schematic of the data structuring and forecast model development used in this study. The first task of Model Identification involved fitting the various autoregressive forecasting schemes to the demand data. First, using a set number of points to prime the models; second, to generate a single predictive period forecast; and third, to recursively add points, refit the regression and generate lead time and procurement cycle forecasts until actual demand periods are exhausted. The Model Identification phase involved processing approximately 7,850 series of subsistence demand history through over 100 autoregressive type models as described in Section III and Appendix N. A typical iterative autoregression report is provided in Table 5.

Table 5 depicts the fitting of an integrated autoregressive harmonic model to the demand series for Pork Spareribs stocked at Bremerhaven, Germany. The predictor period is six months, i.e., six month sums of demand are used to estimate the lead time and procurement cycle demand.

The key statistics in Table 5 are given in the RESULTS area at the bottom of the report. It is important to note that the Mean Absolute Deviation (MAD) and the Mean Absolute Percentage Error (MAPE) are generally considerably less for the subject model (IFCT) than the present DLA model (DFCT). The MAD and MAPE are measures of forecast accuracy. Appendix B provides a detailed description of the terms in the autoregression report.

The fact that the subject model, which is seasonal, has been more accurate in forecasting this item's demand would indicate that the demand pattern may be seasonal. It must be considered that six parameters were required to generate this model. A simpler model may identify the seasonal pattern and perform just as well.

After developing the report in Table 5, the nomenclature and other item data, the actual lead time and procurement cycle demand, and the forecast errors from the autoregressive models are stored for further analysis.

In summary, Table 5 provides a report for comparing various autoregressive forecasting models against the present DLA method. Various statistical measures of forecast accuracy such as mean absolute deviation, mean error, and mean absolute percentage error are given to assist the analyst in reviewing various autoregressive models.



FIGURE 2

SCHEMATIC OF DATA STRUCTURING  
AND FORECAST MODEL DEVELOPMENT

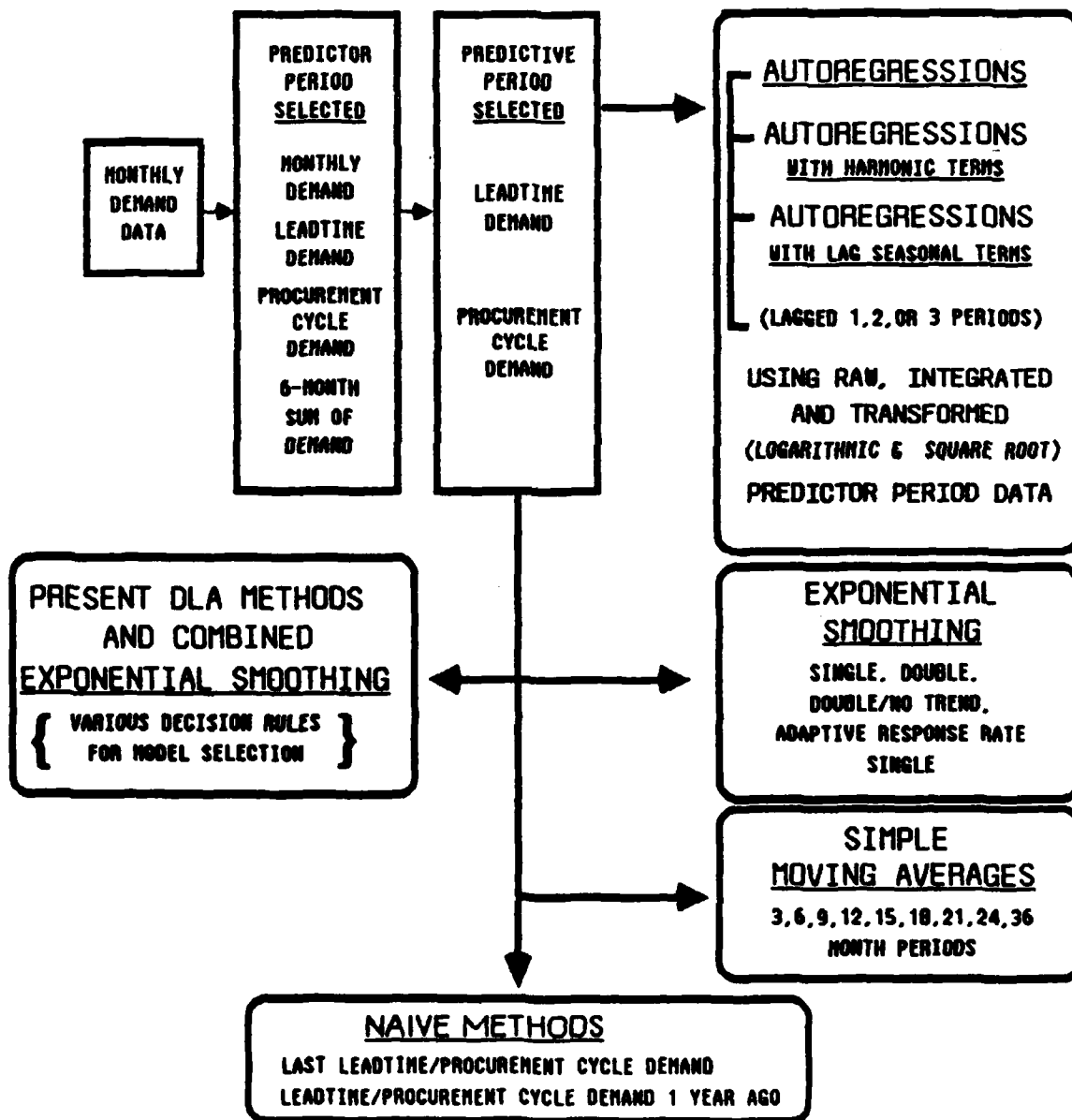


Table 5

## SAMPLE AUTOREGRESSION REPORT

| PERISHABLES         |        |        |        |       |                         |          |       |        |       | MODEL = 24                  |        |       |       |        |       |      |      |      |      |
|---------------------|--------|--------|--------|-------|-------------------------|----------|-------|--------|-------|-----------------------------|--------|-------|-------|--------|-------|------|------|------|------|
| NSN                 | PCK    | DEP    | LT     | PC    | NOMENCLATURE            | CONSTANT | NDP   | ITEM # |       |                             |        |       |       |        |       |      |      |      |      |
| 8905001268743       | 1      | LB     | 3      | 1     | PORK, SPARERIBS, FROZEN |          | 71    | 1397   |       |                             |        |       |       |        |       |      |      |      |      |
| LEAD TIME ESTIMATES |        |        |        |       |                         |          |       |        |       | PROCUREMENT CYCLE ESTIMATES |        |       |       |        |       |      |      |      |      |
| MONTH:              | ACT    | IFCT   | ERR    | % ERR | DFT                     | ERR      | % ERR | IFCT   | ACT   | IFCT                        | ERR    | % ERR | DFT   | ERR    | % ERR |      |      |      |      |
| 36:                 | 226438 | 204500 | 21938  | .10   | 208897                  | 19541    | .09   | 36:    | 66133 | 53918                       | 12215  | .18   | 68966 | -2833  | -.04  |      |      |      |      |
| 37:                 | 204984 | 191038 | 13946  | .07   | 240344                  | -35360   | -.17  | 37:    | 54132 | 69969                       | -15837 | -.29  | 80115 | -25983 | -.48  |      |      |      |      |
| 38:                 | 182799 | 196577 | -13778 | -.08  | 231189                  | -48390   | -.26  | 38:    | 41677 | 68802                       | -27125 | -.65  | 77063 | -35386 | -.85  |      |      |      |      |
| 39:                 | 161942 | 222118 | -60176 | -.37  | 207020                  | -45078   | -.28  | 39:    | 58331 | 53405                       | 4926   | .08   | 69007 | -10676 | -.18  |      |      |      |      |
| 40:                 | 154140 | 207975 | -53835 | -.35  | 201692                  | -47552   | -.31  | 40:    | 46678 | 50538                       | -3860  | -.08  | 67231 | -20553 | -.44  |      |      |      |      |
| 41:                 | 146686 | 173824 | -27138 | -.19  | 172598                  | -25912   | -.18  | 41:    | 46250 | 38779                       | 7471   | .16   | 57533 | -11283 | -.24  |      |      |      |      |
| 42:                 | 151259 | 149625 | 1634   | .01   | 143486                  | 7773     | .05   | 42:    | 59376 | 52474                       | 6902   | .12   | 47829 | 11547  | .19   |      |      |      |      |
| 43:                 | 152304 | 165209 | -12905 | -.08  | 164567                  | -12263   | -.08  | 43:    | 59744 | 81677                       | -21933 | -.37  | 54856 | 4888   | .08   |      |      |      |      |
| 44:                 | 165370 | 191141 | -25771 | -.16  | 143360                  | 22010    | .13   | 44:    | 64263 | 71422                       | -7159  | -.11  | 47787 | 16476  | .26   |      |      |      |      |
| 45:                 | 183383 | 210509 | -27126 | -.15  | 145004                  | 38379    | .21   | 45:    | 82558 | 66506                       | 16052  | .19   | 48335 | 34223  | .41   |      |      |      |      |
| 46:                 | 206565 | 213554 | -6989  | -.03  | 165216                  | 41349    | .20   | 46:    | 75146 | 71335                       | 3811   | .05   | 55072 | 20074  | .27   |      |      |      |      |
| 47:                 | 221967 | 212656 | 9311   | .04   | 172301                  | 49666    | .22   | 47:    | 80557 | 60202                       | 20355  | .25   | 57434 | 23123  | .29   |      |      |      |      |
| 48:                 | 238261 | 205087 | 33174  | .14   | 180886                  | 50175    | .21   | 48:    | 36142 | 48514                       | -12372 | -.34  | 62695 | -26553 | -.73  |      |      |      |      |
| 49:                 | 191845 | 196977 | -5132  | -.03  | 227120                  | -35275   | -.18  | 49:    | 32087 | 59903                       | -27816 | -.87  | 75707 | -43620 | -1.36 |      |      |      |      |
| 50:                 | 148786 | 180791 | -32005 | -.22  | 223703                  | -74917   | -.50  | 50:    | 41005 | 46998                       | -5993  | -.15  | 74568 | -33563 | -.82  |      |      |      |      |
| 51:                 | 109234 | 169172 | -59338 | -.55  | 239666                  | -130732  | -1.20 | 51:    | 38505 | 47443                       | -8938  | -.23  | 79989 | -41484 | -.08  |      |      |      |      |
| 52:                 | 111597 | 125674 | -14077 | -.13  | 150135                  | -38538   | -.35  | 52:    | 52460 | 35768                       | 16692  | .32   | 50045 | 2415   | .05   |      |      |      |      |
| 53:                 | 131970 | 115181 | 16789  | .13   | 125223                  | 9447     | .07   | 53:    | 49619 | 41505                       | 8114   | .16   | 40841 | 8778   | .18   |      |      |      |      |
| 54:                 | 140584 | 115284 | 25300  | .18   | 116124                  | 24460    | .17   | 54:    | 53257 | 44305                       | 8952   | .17   | 38708 | 14549  | .27   |      |      |      |      |
| 55:                 | 155336 | 141129 | 14207  | .09   | 113556                  | 41780    | .27   | 55:    | 73837 | 63836                       | 10001  | .14   | 37852 | 35985  | .49   |      |      |      |      |
| 56:                 | 176713 | 181454 | -4741  | -.03  | 144720                  | 32038    | .18   | 56:    | 66592 | 74495                       | -7803  | -.12  | 48225 | 18467  | .28   |      |      |      |      |
| 57:                 | 193786 | 216376 | -22590 | -.12  | 14720                   | 49066    | .25   | 57:    | 68184 | 75039                       | -6855  | -.10  | 48240 | 19944  | .29   |      |      |      |      |
| 58:                 | 208713 | 208266 | 447    | .00   | 157553                  | 51160    | .25   | 58:    | 57585 | 52975                       | 4610   | .08   | 52518 | 5067   | .09   |      |      |      |      |
| 59:                 | 192461 | 182064 | 10397  | .05   | 199112                  | -6651    | -.03  | 59:    | 56003 | 50232                       | 5771   | .10   | 66371 | -10368 | -.19  |      |      |      |      |
| 60:                 | 181772 | 155570 | 26202  | .14   | 196931                  | -15159   | -.08  | 60:    | 50730 | 57244                       | -6514  | -.13  | 65644 | -14914 | .29   |      |      |      |      |
| 61:                 | 164318 | 160603 | 3715   | .02   | 206633                  | -42315   | -.26  | 61:    | 44105 | 50596                       | -6491  | -.15  | 68878 | -24773 | .56   |      |      |      |      |
| 62:                 | 150838 | 154687 | -3849  | -.03  | 182608                  | 31770    | -.21  | 62:    | 30490 | 41576                       | -11086 | -.36  | 60869 | -30379 | -1.00 |      |      |      |      |
| 63:                 | 125325 | 141645 | -16320 | -.13  | 174890                  | -49565   | -.40  | 63:    | 35635 | 35545                       | 90     | .00   | 58297 | -22662 | -.64  |      |      |      |      |
| 64:                 | 110230 | 124134 | -13904 | -.13  | 158254                  | -48024   | -.44  | 64:    | 42078 | 32800                       | 9278   | .22   | 52751 | -10673 | -.25  |      |      |      |      |
| 65:                 | 108203 | 122500 | -14297 | -.13  | 141576                  | -33373   | -.31  | 65:    | 49506 | 50715                       | -1209  | -.02  | 47192 | 2314   | .05   |      |      |      |      |
| 66:                 | 127219 | 129093 | -1874  | -.01  | 108398                  | 18821    | .15   | 66:    | 48760 | 48280                       | 480    | .01   | 36133 | 12627  | .26   |      |      |      |      |
| 67:                 | 140344 | 144743 | -4399  | -.03  | 108567                  | 31777    | .23   | 67:    | 42259 | 55552                       | -13293 | -.31  | 36189 | 6070   | .14   |      |      |      |      |
| 68:                 | 140525 | 150068 | -9543  | -.07  | 117218                  | 23307    | .17   | 68:    | 41008 | 59136                       | -18128 | -.44  | 39073 | 1935   | .05   |      |      |      |      |
| 69:                 | 132027 | 168005 | -35978 | -.27  | 137868                  | -5841    | -.04  | 69:    | 48573 | 65227                       | -16554 | -.34  | 45956 | 2617   | .05   |      |      |      |      |
| 70:                 | 131840 | 179872 | -48032 | -.36  | 143312                  | -11472   | -.09  | 70:    | 46010 | 62245                       | -16235 | -.35  | 47771 | -1761  | .04   |      |      |      |      |
| 71:                 | 135591 | 184094 | -48503 | -.36  | 133651                  | 1940     | .01   | 71:    | 701   | 29848                       | -19044 | -.64  | 44550 | -14702 | -.49  |      |      |      |      |
| 72:                 | 124431 | 166873 | -42442 | -.34  | 127526                  | -3095    | -.02  | 72:    | 33102 | 30339                       | 2763   | .08   | 42509 | -9407  | -.28  |      |      |      |      |
| 73:                 | 108960 | 144634 | -35674 | -.33  | 138779                  | -29819   | -.27  | 73:    | 50272 | 26617                       | 23655  | .47   | 46260 | 4012   | .08   |      |      |      |      |
| RESULTS             |        |        |        |       |                         |          |       |        |       | MAD                         |        |       |       |        |       |      |      |      |      |
| MERR                | MAPE   | MERR   | MAPE   | MERR  | MAPE                    | MERR     | MAPE  | MERR   | MAPE  | MERR                        | MAPE   | MERR  | MAPE  | MERR   | MAPE  | MERR | MAPE | MERR | MAPE |
| 21528               | -12209 | 15     | 33784  | -6800 | .22                     | 10960    | -2426 | 23     | 16755 | -3854                       | .36    |       |       |        |       |      |      |      |      |

NO OF FIT PARAMETERS = 6

LEAD TIME PARAMETERS :

PROC CYCLE PARAMETERS :

The next part of Model Identification involves the additional selection of exponential smoothing, moving average, and naive methods to the autoregressive methods. The user may select any combination of these desired. In this study, a wide range of moving averages, exponential smoothing models for different smoothing parameters, and two naive models were investigated. Model evaluation then begins.

#### E. Evaluation Criteria

One goal of a forecasting system is the minimization of the total forecast error incurred over time. Traditionally, squared forecast errors have been a useful measure of accuracy with Mean Squared Error (MSE) recognized as a popular choice.

MSE is defined as follows:

$$MSE = \frac{1}{n} \sum_{t=1}^m (A_t - F_t)^2$$

where:  $A_t$  is the actual demand and  $F_t$  is the forecasted demand.

MSE is closely related to variance and is widely accepted in statistics as a measure of being close. Root Mean Squared Error (RMSE) is the square root of MSE and is closely related to standard deviation.

The squared error measures have the advantage of penalizing large forecast errors and ignoring the sign of the error. One drawback of squared error measures is determining the level of significance between two models. For example, what is the significance of accuracy between an RMSE of 25 and 30? This limitation notwithstanding, the ratio of the RMSE of a test model versus the RMSE of the current DLA method and the standard deviation of this ratio are included as evaluation criteria for model selection. Table 6 is a sample model test set evaluation report. In it, the models are ranked by RMSE and the ratio of the RMSE for the test model and the RMSE for the no-change model (LAST LT/PC). A complete description of the model evaluation report is provided in Appendix E.

There are economic benefits to be gained by demand variance reduction. In DoD inventory models, the total variable cost is the sum of ordering, holding, and stockout costs. A Subsistence Inventory Simulation is not presently available to test the performance of different forecasting models in terms of total inventory costs. However, it has been documented that a particular forecasting model's accuracy (as measured by Mean Squared Error) plays a vital role in keeping total stockout costs reasonable and that holding costs can be reduced by study of the sources of lead time demand variance (Reference 14).

Other evaluation criteria, used in this study, relate to the Theil decomposition of the forecast error into bias, regression, and disturbance proportions. Bias distorts forecast accuracy through systematic overforecasting or underforecasting. When Theil's bias proportion exceeds .2, the model is rejected for selection. For a complete description and application of the Theil decomposition, the reader should review References 15 and 16, respectively.

Table 6

## SAMPLE FORECAST MODEL EVALUATION REPORT

--- PORK, SPARERIBS, FROZEN  
 NSN: 8905001268743 ITEM NO: 00520 LEADTIME: 3 PROC CYCLE: 1 RIC/DEPOT: LB  
 CHILL CODE: 2 SHELF LIFE: 06 VSL: 4 UI: LB NET WGT: 000052 SUPPLY CODE: ISSUE CODE: FLEET CODE: 0  
 MEAN: 176908 STDEV: 38548 MAD: 34201 MEDIAN: 185591 T-MEAN 177343 MAD/SD: .89 C/VAR: .22 C/SKEW: -.09 C/EXC: -1.20  
 TREND 47.3 (DF: 4 F: 29.1) SEAS 34.8 (DF: 11 F: 7.8) RAND 17.9 (DF: 44)

SEAS: 103.7 85.9 81.0 81.9 88.9 95.0 101.1 107.7 115.7 117.7 117.3 104.2  
 TREND: 112.8 115.4 104.5 92.8 74.4

% POS CHANGES: 49.3 48.5 47.7 48.4 46.0 41.9 41.0 40.0 35.6 36.2 28.1 30.4  
 % TURNS: 28.4 22.7 16.9 17.2 17.5 17.7 18.0 16.7 15.3 17.2 21.1 25.0

| RAW DATA    | MEAN   | STDEV | 1     | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | CHI-SQ     |
|-------------|--------|-------|-------|---|---|---|---|---|---|---|---|----|----|----|------------|
|             | 176908 | 38548 | +     | + | + | . | . | . | . | . | + | +  | +  | +  | 124.2 AUTO |
|             |        |       | +     | . | . | . | . | . | . | . | . | .  | .  | .  | 77.8 PART  |
|             |        |       | .     | . | . | . | . | . | . | . | + | +  | +  | +  | 66.2 LAG   |
| RAW INT     | -669   | 20343 | +     | . | . | . | . | . | . | . | . | .  | .  | .  | 73.7       |
| CROSS CORR  |        |       | +     | + | . | . | . | . | . | . | + | +  | +  | +  | 78.5       |
| CROSS INTEG |        |       | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 20.5       |
| -----       |        |       |       |   |   |   |   |   |   |   |   |    |    |    |            |
|             | MEAN   | RMSE  | THEIL |   |   |   |   |   |   |   |   |    |    |    |            |
| INAR3C HARM | -9585  | 24629 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 49.2       |
| INAR2C HARM | -8403  | 25253 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 54.0       |
| INAR1C HARM | -8222  | 27060 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 44.2       |
| LAST YEAR   | -21656 | 32951 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 31.4       |
| NAR3C HARM  | -22469 | 33214 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 31.4       |
| NAR1C LAG   | -20087 | 33316 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 46.00      |
| 12-MO AVG   | -12552 | 33706 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 42.6       |
| NAR2C HARM  | -26156 | 34335 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 116.2      |
| NAR1C HARM  | -27814 | 34520 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 32.1       |
| NAR2C LAG   | -22348 | 35190 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 59         |
| NAR3C LAG   | -22851 | 36481 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 31.5       |
| 18-MO AVG   | -14834 | 38883 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 33.9       |
| DLA         | -5522  | 40339 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 40         |
| INAR3C      | -2539  | 41964 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 15.01      |
| NAR2C       | -30298 | 42587 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 93.4       |
| INAR2C      | -2098  | 42704 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 69         |
| NAR3C       | -32240 | 43220 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 35.8       |
| LAST LT/PC  | -6230  | 43792 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 51.02      |
| NAR1C       | -26192 | 44098 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 29         |
| INAR1C      | -1987  | 44498 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 00         |
| GLOBAL MN   | -27424 | 44747 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 26         |
| 6-MO AVG    | -6895  | 46553 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 73         |
| INAR3C LAG  | -19319 | 54618 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 29         |
| INAR2C LAG  | -21343 | 60108 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 35.844     |
| INAR1C LAG  | -21808 | 65630 | .     | . | . | . | . | . | . | . | . | .  | .  | .  | 28216      |

--- PORK, SPARERIBS, FROZEN  
 NSN: 8905001268743 ITEM NO: 00520 LEADTIME: 3 PROC CYCLE: 1 RIC/DEPOT :LB  
 CHILL CODE: 2 SHELF LIFE: 06 VSL: 4 UI: LB NET WGT: 000062 SUPPLY CODE: ISSUE CODE: FLEET CODE: 0  
 MEAN: 58305 STDEV: 15532 MAD: 13122 MEDIAN: 59139 T-MEAN 58212 MAD/SD: .84 C/VAR: .27 C/SKEW: -.04 C/EXC: -.86  
 TREND 32.3 (DF: 4 F: 10.9) SEAS 35.2 (DF: 11 F: 4.3) RAND 32.6 (DF: 44)

SEAS: 70.9 86.3 92.1 92.2 104.6 110.9 112.2 129.0 117.1 110.7 89.3 84.7  
 TREND: 114.4 108.3 100.7 96.2 73.4

% POS CHANGES: 47.8 50.0 47.7 46.9 49.2 43.5 36.1 33.3 37.3 36.2 35.1 33.9  
 % TURNS: 56.7 27.3 30.8 21.9 22.2 19.4 18.0 18.3 22.0 19.0 33.3 37.5

MEAN STDEV 1 2 3 4 5 6 7 8 9 10 11 12 CHI-SQ

RAW DATA 58305 15532 + + + + + + + + + + + + 78.7 AUTO

+ + + + + + + + + + + + 42.4 PART

+ + + + + + + + + + + + 18.7 LAG

+ + + + + + + + + + + + 11.7

+ + + + + + + + + + + + 56.0

+ + + + + + + + + + + + 34.1

\* RAW INT  
 CROSS CORR  
 CROSS INTEG

MEAN RMSE THEIL  
 12-MO AVG -5470 14320 .69  
 NAR1C LAG -8422 15328 .73  
 \* LAST YEAR -7297 15369 .74  
 NAR2C LAG -9836 15806 .76  
 18-MO AVG -8230 16014 .77  
 INAR3C HARM -5224 16585 .79  
 NAR3C LAG -10823 16885 .81  
 INAR2C HARM -5227 17438 .83  
 GLOBAL MN -10427 17689 .85  
 NAR3C HARM -8865 17721 .85  
 INAR1C HARM -4422 17962 .86  
 NAR2C -13665 18098 .87  
 NAR1C -12690 18217 .87  
 NAR2C HARM -10066 18496 .89  
 6-MO AVG -3584 18589 .89  
 INAR3C -2149 18890 .90  
 NAR1C HARM -11703 19081 .91  
 NAR3C -15097 19576 .94  
 DLA -3126 20181 .97  
 LAST LT/PC -2890 20892 1.00  
 INAR2C -2527 21102 1.01  
 INAR3C LAG -9117 21110 1.01  
 INAR1C -2641 22480 1.08  
 INAR2C LAG -9620 22660 1.08  
 INAR1C LAG -9466 23776 1.14

Table 6  
 (continued)

BIAS REGR DIST OLC RMSE OLC THEIL  
 .15 .00 .85 13188 .63  
 .31 .00 .69 12759 .61  
 .23 .16 .61 12036 .58  
 .39 .03 .58 12027 .58  
 .15 .03 .82 14500 .69  
 .10 .20 .70 13827 .66  
 .42 .04 .55 12476 .60  
 .09 .26 .65 14046 .67  
 .35 .03 .62 13896 .67  
 .25 .13 .62 13910 .67  
 .06 .30 .64 14316 .69  
 .58 .03 .39 11319 .54  
 .49 .07 .44 12092 .58  
 .30 .11 .59 14198 .68  
 .04 .32 .64 14849 .71  
 .01 .37 .62 14829 .71  
 .38 .08 .53 13946 .67  
 .60 .00 .40 12366 .59  
 .117 .1 .02 .43 .54 14877 .71  
 .02 .47 .51 14876 .71  
 .01 .50 .49 14775 .71  
 .19 .44 .37 12921 .62  
 .117 .5 .01 14612 .70  
 .18 .47 .34 13309 .64  
 .16 .51 .33 13668 .65

During the evaluation phase, extensive testing was performed on the present DLA use of exponential smoothing for semiperishable subsistence. The present formula uses smoothing constants of .1, .15, and .2 (.2 only for brand name items) and simply extends the one period ahead double exponential smoothed forecast through the lead time and procurement cycle.

The decision rule to switch the smoothing constant is made on the forecast formula which has the least smoothed mean absolute deviation through the last month. The current DLA formulation, on the average, outperformed true double exponential smoothing for semiperishable subsistence; however, it was consistently less effective than single exponential smoothing.

These findings led to the testing of various decision rules for selecting the smoothing constant and the kind of exponential smoothing (single, DLA formulation, and double). A combined exponential smoothing model was designed originally as a conglomerate of 18 exponential smoothing models (single, DLA formulation, and double) for smoothing constants .05, .1, .15, .2, .25, and .30.

The following decision rules on switching models within the COMBINED model were tested:

1. Select on least smoothed MAD over the last lead time or procurement cycle, respectively, with a smoothing constant of .1.
2. Select on least smoothed MAD over the last lead time or procurement cycle, respectively, with the smoothing constant presently in use.
3. Select on least smoothed squared error over the last lead time or procurement cycle, with a smoothing constant of .1.
4. Select on least smoothed squared error of the last lead time or procurement cycle, respectively, with the smoothing constant presently in use.

Model assignment analyses (described in next section) were then made on a sample of 800 series. Decision rules 1 and 3 were found to be superior to 2 and 4 in terms of reduced RMSE and compactness distribution. Decision rule 1 was slightly better than rule 3 in terms of reduced RMSE and the number of series with a positive improvement.

Analyses were then performed on the smoothing constant to test if changing the constant for smoothing the MAD would improve forecast accuracy for decision rule 1. Model assignment analyses were performed for smoothing constants of .05, .1, and .2. The smoothing constant of .2 performed slightly better than the others in terms of reduced RMSE and number of series with a positive improvement.

Smoothing the MAD with a constant uses the same set of weights for the errors of any of the models. When an  $\alpha$  of .2 is employed, 74 percent ( $1-(.8)^6$ ) of the weights used in the smoothed MAD is given to the last six errors while 93 percent ( $1-(.8)^{12}$ ) is given to the last 12 errors.

The combined exponential smoothing method throughout this report will be denoted as COMBINED.

The original COMBINED model performed better than any other individual model when assigned to semiperishable subsistence demand series. However, it was rather cumbersome. Further testing indicated that the range of exponential smoothing formulations and smoothing constants could be narrowed down without appreciable deterioration in forecast accuracy for the COMBINED model. When the COMBINED model was limited to the single and DLA formulations for exponential smoothing with smoothing constants of .1, .2, and .3, a deterioration of only .7 percent in average RMSE was realized.

This results in a reduction of data storage requirements from 36 to 12 values per item/warehouse record for this model.

The model evaluation phase provided a means to rank the various forecast models according to statistical accuracy. At the completion of the model evaluation phase there was enough information available to begin to study the problem of assigning forecast models to classes of subsistence items.

#### F. Model Assignment Analysis

##### 1. Demonstration of the Model Assignment Analysis Technique

This section of the report describes how forecast model assignments to item classes were designed and tested. Model assignment includes the study of the performance of any one over a hundred individual models to the more difficult problem of the interaction of competing models in a group. For example, if two models perform the same on most items, it is probably feasible to assign one. However, if two models perform well on distinctly different items, their performance as a group will be considerably enhanced.

All model assignment analysis performance statistics are relative to a base model. In the model assignment analyses in this report, the base model was chosen as the current DLA method. For demonstration purposes, the model assignment analysis for perishable subsistence is described here. The model assignment analysis for semiperishable subsistence is provided in Appendix D.

The final model assignment analysis report for perishable subsistence is provided for demonstration purposes. The model assignment report contains nine tables which are used to construct and test groups of forecast models for the subsistence commodity.

Table 7 provides the input specifications for the model assignment analysis. Information following the @ indicates the identification of the test under study. FORECAST file indicates the Fortran device assigned for the input file from the Model Evaluation Phase. Model TITLES file indicates the Fortran device assigned for the Model Titles. Select is an option to sort on brand name, troop issue, or not. Post-forecast Theil adjustment is an option selected to estimate magnitude of improvement when unsatisfactory models are corrected for bias and regression errors. Random residual check may be used to constrain model assignment. The Base Model is the present DLA forecast formulation or whatever other model the user may choose. The performance in the test set of all model assignments will be made relevant to the base model's performance. The CHI-Square Limitation may be used to provide a certain confidence level for randomness in the residuals.

Table 7

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
INPUT SPECIFICATIONS

## ANALYSIS INPUT DATA

1 TRACKING BASED ON MAD SMOOTHED WITH CONSTANT ALPHA OF .2  
 9 PERISHABLE SUBSISTENCE  
 8 FINAL MODEL GROUP

FORECAST FILE: 7

MODEL TITLES FILE: 11

SELECT: ALL

POST-FORECAST THEIL ADJUSTMENT: NONE

RANDOM RESIDUAL CHECK: NO

BASE MODEL (20): DLA

CHI-SQUARE LIMITATION: NONE

|                 |                |              |                |               |               |
|-----------------|----------------|--------------|----------------|---------------|---------------|
| MODELS ON FILE: | 1: GLOBAL MEAN | 2: 12-MO AVG | 3: 24-MO AVG   | 4: 36-MO AVG  | 5: SES(.05)   |
|                 | 6: SES(.10)    | 7: SES(.15)  | 8: SES(.20)    | 9: SES(.25)   | 10: SES(.30)  |
|                 | 11: DES(.10)   | 12: DES(.20) | 13: DES(.30)   | 14: ARRS(.10) | 15: ARRS(.20) |
|                 | 16: ARRS(.30)  | 17: COMBINED | 18: LAST LT/PC | 19: LAST YEAR | 20: DLA       |
|                 | 21: AR1 LAG    | 22: NAR1 LAG | 23: LAR1 LAG   | 24: LNAR1 LAG | 25: SAR1 LAG  |
|                 | 26: SNAR1 LAG  |              |                |               |               |

ANALYZED MODELS: 2: 12-MO AVG 7: SES(.15) 18: LAST LT/PC 19: LAST YEAR 21: AR1 LAG



The MODELS ON FILE are those generated from the identification and evaluation phase. See Appendix N for formulas and acronyms. The Analyzed models are the set which are selected to be assigned across the class of items under study resulting in an improvement or degradation in performance over the base model.

Table 8 demonstrates the assignment occurrence and individual assignment distribution matrices. For this class of items (perishable), and the predictive period (lead time) under study, the assignment occurrence table provides the frequency of occurrence of the best and second best model in terms of RMSE reduction. Models asterisked are those assigned in the analysis.

For example, the unanalyzed model 3 - (24-MO AVG) was better 240 times than the assigned model 7 - (SES(.15)) when model 7 was selected best (823 times).

The Prefer row indicates how often each unanalyzed model would be preferred to any of the assigned models. This is the sum of the columns of the occurrence matrix.

The Accept row indicates how frequently the assigned models were first or second, (e.g., 2 times the number of series being tested). The assign row indicates the best assignment among the analyzed models.

The average standard deviation index is the sum over the item class of the ratio of assigned model RMSE to base model RMSE. The number of series in the item class is also noted. The individual distribution table provides the performance distribution in deciles from -100 to 100 for each model on the file when individually assigned to the entire class of items under study. Performance is defined as the average percentage reduction in RMSE as compared to the base model. For the example, the RMSE of model 3 (24-month average) was 40 to 50% less than RMSE of the base model four times for the 1993 series under study. At the same time, the RMSE of model 3 was 40 to 50 percent greater than the RMSE of the base model 17 times.

The first matrix on Table 9 shows the performance measured by lower average ratios of assigned model RMSE to base model RMSE of individual vs. base model when each model is individually assigned across the entire class of items. The second row of this matrix indicates the standard deviation about the mean of the individual performances. The third row of this matrix provides the number of standard deviations around 100 percent wherein the mean performance lies, e.g., (  $100 - \text{PERF}$  ). The second matrix of Table 9 depicts the percentage in

STD

base RMSE performance distribution in deciles from -100 to 100 and the reduction in Base RMSE for assigned model to the subclass where they are assigned. For example, for the 796 times the 12-MO average model was assigned an average reduction of 22 percent in RMSE was achieved over the base model for those 796 demand series.

Table 10 provides the assignment contribution matrix which is critical to the testing of the assigned group of models. The assignment contribution matrix is a tool which can be used to show whether additional performance may be gained by adding or switching models.

In the study of the assignment contribution it is important to remember the distinction between the assigned and unanalyzed models on the file.

Table 8

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
LEAD TIME DEMAND - ASSIGNMENT OCCURRENCE AND  
INDIVIDUAL ASSIGNMENT DISTRIBUTION MATRICES

| TROOP ISSUE AND BRAND NAME                  |     | 1    | 2   | 3   | 4   | 5   | 6   | 7    | 8    | 9   | 10   | 11   | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20   |
|---|-----|------|-----|-----|-----|-----|-----|------|------|-----|------|------|-----|-----|-----|-----|-----|-----|-----|-----|------|
| LEADTIME                                    |     | 21   | 22  | 23  | 24  | 25  | 26  |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| 2*  | 206 | 796  | 238 | 200 | 206 | 179 | 715 | 46   | 40   | 34  | 31   | 5    | 0   | 53  | 16  | 4   | 96  | 2   | 35  | 4   |      |
|   | 44  | 20   | 7   | 16  | 13  | 18  |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| 7*  | 270 | 684  | 240 | 245 | 275 | 392 | 823 | 323  | 272  | 233 | 81   | 23   | 3   | 104 | 84  | 46  | 265 | 115 | 0   | 33  |      |
|   | 24  | 14   | 5   | 21  | 9   | 20  |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| 18*   | 8   | 11   | 2   | 4   | 13  | 6   | 122 | 36   | 70   | 89  | 23   | 29   | 1   | 21  | 55  | 49  | 57  | 168 | 0   | 76  |      |
|   | 35  | 5    | 5   | 11  | 8   | 8   |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| 19*   | 2   | 27   | 8   | 3   | 1   | 0   | 2   | 0    | 0    | 0   | 0    | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 72  | 0    |
|   | 43  | 3    | 3   | 5   | 5   | 7   |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| 21*   | 13  | 44   | 12  | 12  | 9   | 4   | 34  | 5    | 6    | 8   | 6    | 3    | 2   | 7   | 4   | 3   | 10  | 21  | 35  | 14  |      |
|   | 134 | 27   | 32  | 30  | 64  | 36  |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| PREFER                                      | 499 | 0    | 500 | 465 | 504 | 581 | 0   | 410  | 388  | 364 | 141  | 60   | 6   | 185 | 159 | 102 | 428 | 0   | 0   | 127 |      |
|   | 0   | 69   | 52  | 83  | 99  | 89  |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| ACCEPT                                      | 0   | 1562 | 0   | 0   | 0   | 0   | 0   | 1696 | 0    | 0   | 0    | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 306 | 142 | 0    |
|   | 280 | 0    | 0   | 0   | 0   | 0   | 0   | 0    |      |     |      |      |     |     |     |     |     |     |     |     |      |
| ASSIGN                                      | 0   | 796  | 0   | 0   | 0   | 0   | 0   | 823  | 0    | 0   | 0    | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 168 | 72  | 0    |
|   | 134 | 0    | 0   | 0   | 0   | 0   | 0   | 0    |      |     |      |      |     |     |     |     |     |     |     |     |      |
| AVERAGE STD DEV INDEX (BASE MODEL 20): 83.2 |     |      |     |     |     |     |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| 1993 SERIES ACCEPTED                        |     |      |     |     |     |     |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| REDUCTION IN BASE RMSE                      |     |      |     |     |     |     |     |      |      |     |      |      |     |     |     |     |     |     |     |     |      |
| MODEL                                       | 100 | 90   | 80  | 70  | 60  | 50  | 40  | 30   | 20   | 10  | 0    | -10  | -20 | -30 | -40 | -50 | -60 | -70 | -80 | -90 | -100 |
| 1:  | 0   | 0    | 0   | 0   | 0   | 1   | 7   | 133  | 338  | 449 | 347  | 225  | 139 | 95  | 57  | 51  | 30  | 21  | 16  | 18  | 66   |
| 2:  | 0   | 0    | 0   | 0   | 0   | 1   | 4   | 142  | 508  | 608 | 404  | 151  | 87  | 43  | 23  | 13  | 7   | 0   | 1   | 0   | 2    |
| 3:  | 0   | 0    | 0   | 0   | 0   | 1   | 4   | 160  | 415  | 540 | 351  | 225  | 106 | 78  | 35  | 17  | 19  | 13  | 7   | 5   | 17   |
| 4:  | 0   | 0    | 0   | 0   | 0   | 1   | 8   | 131  | 388  | 457 | 369  | 209  | 151 | 77  | 62  | 36  | 24  | 12  | 9   | 13  | 47   |
| 5:  | 0   | 0    | 0   | 0   | 0   | 1   | 5   | 133  | 386  | 510 | 381  | 203  | 130 | 68  | 49  | 35  | 23  | 13  | 12  | 6   | 38   |
| 6:  | 0   | 0    | 0   | 0   | 0   | 2   | 118 | 512  | 665  | 387 | 164  | 66   | 30  | 24  | 8   | 6   | 6   | 1   | 2   | 2   | 2    |
| 7:  | 0   | 0    | 0   | 0   | 0   | 1   | 74  | 522  | 768  | 399 | 142  | 56   | 17  | 8   | 3   | 0   | 0   | 0   | 3   | 0   | 0    |
| 8:  | 0   | 0    | 0   | 0   | 0   | 0   | 32  | 465  | 857  | 443 | 146  | 37   | 9   | 1   | 1   | 2   | 0   | 0   | 0   | 0   | 0    |
| 9:  | 0   | 0    | 0   | 0   | 0   | 0   | 6   | 352  | 948  | 518 | 138  | 26   | 3   | 0   | 2   | 0   | 0   | 0   | 0   | 0   | 0    |
| 10:   | 0   | 0    | 0   | 0   | 0   | 0   | 1   | 215  | 1009 | 618 | 134  | 13   | 3   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 11:   | 0   | 0    | 0   | 0   | 0   | 0   | 21  | 295  | 750  | 555 | 202  | 96   | 38  | 22  | 9   | 3   | 0   | 0   | 0   | 1   | 1    |
| 12:   | 0   | 0    | 0   | 0   | 0   | 0   | 0   | 3    | 291  | 975 | 532  | 158  | 28  | 6   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 13:   | 0   | 0    | 0   | 0   | 0   | 0   | 0   | 0    | 1    | 129 | 1117 | 622  | 117 | 7   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 14:   | 0   | 0    | 0   | 0   | 0   | 0   | 37  | 373  | 722  | 521 | 198  | 78   | 34  | 18  | 7   | 3   | 0   | 0   | 0   | 1   | 1    |
| 15:   | 0   | 0    | 0   | 0   | 0   | 0   | 1   | 106  | 663  | 766 | 354  | 85   | 16  | 2   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 16:   | 0   | 0    | 0   | 0   | 0   | 0   | 0   | 1    | 7    | 278 | 951  | 639  | 109 | 8   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 17:   | 0   | 0    | 0   | 0   | 0   | 0   | 1   | 80   | 430  | 692 | 555  | 204  | 28  | 3   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 18:   | 0   | 0    | 0   | 0   | 0   | 0   | 0   | 0    | 7    | 100 | 818  | 909  | 143 | 16  | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 19:   | 0   | 0    | 1   | 2   | 1   | 5   | 8   | 31   | 99   | 185 | 321  | 329  | 281 | 246 | 171 | 100 | 54  | 36  | 33  | 26  | 64   |
| 20:   | 0   | 0    | 0   | 0   | 0   | 0   | 0   | 0    | 0    | 0   | 0    | 1993 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 21:   | 0   | 0    | 0   | 0   | 0   | 2   | 6   | 26   | 85   | 259 | 498  | 576  | 308 | 119 | 38  | 25  | 14  | 12  | 8   | 2   | 13   |
| 22:   | 0   | 0    | 0   | 2   | 0   | 3   | 3   | 24   | 105  | 335 | 561  | 491  | 236 | 100 | 44  | 26  | 16  | 9   | 9   | 8   | 21   |

Table 8 (Continued)

|     |   |   |   |   |   |   |    |     |     |     |     |     |     |     |    |    |    |    |    |    |
|-----|---|---|---|---|---|---|----|-----|-----|-----|-----|-----|-----|-----|----|----|----|----|----|----|
| 23: | 0 | 0 | 0 | 0 | 0 | 3 | 16 | 56  | 164 | 357 | 501 | 379 | 201 | 123 | 74 | 37 | 25 | 16 | 13 | 26 |
| 24: | 0 | 0 | 1 | 0 | 0 | 5 | 17 | 84  | 278 | 578 | 525 | 272 | 102 | 49  | 22 | 17 | 10 | 8  | 3  | 21 |
| 25: | 0 | 0 | 2 | 0 | 2 | 6 | 22 | 82  | 269 | 499 | 562 | 313 | 124 | 44  | 27 | 11 | 9  | 10 | 0  | 11 |
| 26: | 0 | 0 | 2 | 0 | 2 | 4 | 24 | 106 | 330 | 589 | 510 | 220 | 97  | 40  | 14 | 15 | 11 | 5  | 7  | 17 |

Table 9

## MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:

## LEAD TIME DEMAND - INDIVIDUAL VS.

BASE MODEL PERFORMANCE AND  
PERFORMANCE OF ASSIGNMENT ALLOCATION

## INDIVIDUAL MODEL V.S. BASE MODEL

|       | 1     | 2     | 3     | 4     | 5     | 6    | 7    | 8    | 9    | 10   | 11   | 12    | 13   | 14   | 15   | 16   | 17    | 18    | 19    | 20 |
|-------|-------|-------|-------|-------|-------|------|------|------|------|------|------|-------|------|------|------|------|-------|-------|-------|----|
|       | 21    | 22    | 23    | 24    | 25    | 26   |      |      |      |      |      |       |      |      |      |      |       |       |       |    |
| 102.4 | 88.0  | 92.8  | 97.9  | 96.3  | 88.0  | 86.7 | 86.9 | 87.6 | 88.6 | 91.4 | 98.3 | 108.7 | 90.0 | 93.6 | 98.0 | 87.3 | 100.6 | 115.7 | 100.0 |    |
| 103.7 | 102.7 | 111.9 | 103.4 | 103.3 | 101.5 |      |      |      |      |      |      |       |      |      |      |      |       |       |       |    |
| 39.8  | 15.8  | 23.3  | 31.4  | 30.6  | 15.9  | 12.0 | 10.0 | 8.6  | 7.5  | 13.6 | 8.7  | 6.6   | 13.3 | 9.4  | 7.5  | 10.4 | 6.8   | 32.3  | .0    |    |
| 21.5  | 24.6  | 24.1  | 21.5  | 18.8  | 20.7  |      |      |      |      |      |      |       |      |      |      |      |       |       |       |    |
| -.06  | .76   | .31   | .07   | .12   | .75   | 1.10 | 1.31 | 1.44 | 1.53 | .63  | .20  | -1.32 | .75  | .68  | .26  | 1.22 | .08   | .49   | .00   |    |
| -.17  | -.11  | -.49  | -.16  | -.17  | -.07  |      |      |      |      |      |      |       |      |      |      |      |       |       |       |    |

## REDUCTION IN BASE RMSE FOR ASSIGNED MODELS

| MODEL | 100 | 90 | 80 | 70 | 60 | 50 | 40  | 30  | 20  | 10  | 0   | -10 | -20 | -30 | -40 | -50 | -60 | -70 | -80 | -90 | -100 |
|-------|-----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 2:    | 0   | 0  | 0  | 0  | 0  | 0  | 4   | 126 | 363 | 241 | 58  | 4   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 7:    | 0   | 0  | 0  | 0  | 0  | 0  | 1   | 12  | 166 | 394 | 215 | 34  | 1   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 18:   | 0   | 0  | 0  | 0  | 0  | 0  | 0   | 3   | 13  | 76  | 75  | 1   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 19:   | 0   | 1  | 2  | 1  | 5  | 6  | 19  | 28  | 8   | 2   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 21:   | 0   | 0  | 0  | 0  | 0  | 3  | 11  | 22  | 46  | 38  | 12  | 2   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
|       | 0   | 1  | 2  | 1  | 5  | 14 | 168 | 581 | 703 | 389 | 125 | 4   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |

Table 10

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
LEAD TIME DEMAND - ASSIGNMENT CONTRIBUTION MATRIX

| ASSIGNMENT CONTRIBUTION |     |       |      |     |       |     |     |     |     |      |  |  |  |  |  |  |  |  |  |  |  |
|-------------------------|-----|-------|------|-----|-------|-----|-----|-----|-----|------|--|--|--|--|--|--|--|--|--|--|--|
| 1                       | 499 | 4.6   | 1.2  | 1.2 |       |     |     |     |     |      |  |  |  |  |  |  |  |  |  |  |  |
| 2                       | 796 | 3.1   | -1.2 | 3   | -1.2  |     |     |     |     |      |  |  |  |  |  |  |  |  |  |  |  |
| 3                       | 500 | 4.2   | 1.0  | 1.6 | 3     | 1.0 |     |     |     |      |  |  |  |  |  |  |  |  |  |  |  |
| 4                       | 465 | 4.7   | 1.1  | 1.4 | 2     | 1.5 | 1.1 |     |     |      |  |  |  |  |  |  |  |  |  |  |  |
| 5                       | 504 | 4.3   | 1.1  | 1.7 | 3     | 1.7 | 1.7 | 1.1 |     |      |  |  |  |  |  |  |  |  |  |  |  |
| 6                       | 581 | 1.8   | 5    | 1.3 | -3    | 1.2 | 1.3 | 1.3 | .5  |      |  |  |  |  |  |  |  |  |  |  |  |
| 7                       | 823 | 3.8   | -1.6 | 3   | -13.5 | 1   | 2   | 3   | 1   | -1.6 |  |  |  |  |  |  |  |  |  |  |  |
| 8                       | 410 | 1.6   | 3    | 1.5 | -8    | 1.4 | 1.4 | 1.4 | .9  | .0   |  |  |  |  |  |  |  |  |  |  |  |
| 9                       | 388 | 2.5   | 5    | 1.6 | -7    | 1.5 | 1.6 | 1.5 | 1.0 | .0   |  |  |  |  |  |  |  |  |  |  |  |
| 10                      | 364 | 2.8   | 5    | 1.7 | -7    | 1.5 | 1.6 | 1.6 | 1.0 | -.2  |  |  |  |  |  |  |  |  |  |  |  |
| 11                      | 141 | 3.7   | 3    | 1.4 | -9    | 1.3 | 1.4 | 1.4 | .8  | -1.0 |  |  |  |  |  |  |  |  |  |  |  |
| 12                      | 60  | 3.4   | 1    | 1.3 | -1.1  | 1.1 | 1.2 | 1.2 | .6  | -1.4 |  |  |  |  |  |  |  |  |  |  |  |
| 13                      | 6   | 4.0   | 0    | 1.2 | -1.2  | 1.1 | 1.1 | 1.1 | .6  | -1.5 |  |  |  |  |  |  |  |  |  |  |  |
| 14                      | 185 | 3.3   | 3    | 1.5 | -8    | 1.3 | 1.4 | 1.4 | .8  | -.8  |  |  |  |  |  |  |  |  |  |  |  |
| 15                      | 159 | 4.2   | 3    | 1.5 | -9    | 1.4 | 1.4 | 1.4 | .9  | -.9  |  |  |  |  |  |  |  |  |  |  |  |
| 16                      | 102 | 3.9   | 2    | 1.4 | -1.0  | 1.2 | 1.3 | 1.3 | .7  | -1.2 |  |  |  |  |  |  |  |  |  |  |  |
| 17                      | 428 | 3.1   | 7    | 1.7 | -3    | 1.6 | 1.7 | 1.6 | 1.1 | .0   |  |  |  |  |  |  |  |  |  |  |  |
| 18                      | 168 | 9.7   | -8   | 4   | -2.1  | 2   | 3   | 3   | -3  | -3.2 |  |  |  |  |  |  |  |  |  |  |  |
| 19                      | 72  | -12.5 | -5   | 7   | -1.8  | .6  | .7  | .6  | .1  | -2.0 |  |  |  |  |  |  |  |  |  |  |  |
| 20                      | 127 | 3.3   | 2    | 1.4 | -1.0  | 1.2 | 1.3 | 1.3 | .7  | -1.3 |  |  |  |  |  |  |  |  |  |  |  |
| 21                      | 134 | -7.2  | -5   | 7   | -1.9  | .6  | .7  | .6  | .1  | -2.2 |  |  |  |  |  |  |  |  |  |  |  |
| 22                      | 69  | 3.3   | 1    | 1.3 | -1.1  | 1.1 | 1.2 | 1.2 | .6  | -1.4 |  |  |  |  |  |  |  |  |  |  |  |
| 23                      | 52  | 5.0   | 1    | 1.3 | -1.1  | 1.2 | 1.2 | 1.2 | .7  | -1.4 |  |  |  |  |  |  |  |  |  |  |  |
| 24                      | 83  | 4.9   | 2    | 1.4 | -1.0  | 1.2 | 1.3 | 1.3 | .7  | -1.3 |  |  |  |  |  |  |  |  |  |  |  |
| 25                      | 99  | 2.4   | 1    | 1.3 | -1.1  | 1.2 | 1.2 | 1.2 | .7  | -1.4 |  |  |  |  |  |  |  |  |  |  |  |
| 26                      | 89  | 3.4   | 2    | 1.3 | -1.0  | 1.2 | 1.3 | 1.2 | .7  | -1.4 |  |  |  |  |  |  |  |  |  |  |  |
|                         |     |       |      |     |       |     |     |     |     |      |  |  |  |  |  |  |  |  |  |  |  |

The first column of the matrix in Table 10 provides the model number. The second column contains the assignment frequency for assigned models or the frequency which the unanalyzed models outperformed any in the assigned group for the unanalyzed models. For example, 796 times out of 1993, model 2 (12 month average) outperformed any in the assigned group.

The third column provides the percentage improvement in base RMSE over the assigned group for the unanalyzed models on those series they performed better. For models in the assigned group, the third column provides the average loss of performance on the assigned subclass of items if the model were deleted from the assigned group.

For unanalyzed models, the fourth column contains the additional average performance to be gained across the entire class of items if the unanalyzed model were added to the subgroup. For assigned models, the fourth column contains the loss of performance across the entire class of items should the models be deleted from the group. With column 5, the assignment switching matrix (# models x # models) begins. The purpose of the assignment switching matrix is to perform sensitivity analyses on the selection of the assigned model group with at most two models at a time. The diagonal of the assignment switching matrix is equivalent to column 4. An example of the use of the assignment switching matrix is as follows:

a. Both models 1 and 5 (global mean and SES(.05)) are unanalyzed in the test group. Individually, adding model 1 would provide a 1.2 percent additional reduction in RMSE while individually, model 5 could add 1.1 percent. However, the additional performance (1.7 percent) achieved by including both models is not additive. This indicates that often both the global mean and SES(.05) perform similarly on most items which is not surprising. Performance can be additive when the two models perform well on distinctly different series.

b. Models 7 (SES(.15)) and 19 (LAST YEAR) are both assigned. If model 7 was deleted from the assigned group, a 1.6 percent reduction in performance would be encountered. If model 19 was deleted from the group, a .5 percent reduction is expected. However, when both are deleted, a 2.0 percent reduction in performance would be encountered. This indicates that model 19 is performing well when model 7 isn't and that the effects of their deletion is almost additive.

c. Model 7 (SES(.15)) is assigned, however, model 12 (DES(.20)) is not. To measure the effect of switching models 7 and 12, go to row 12, column 11, of the assignment contribution matrix (-1.4). This indicates that if DES(.20) were substituted for SES(.15) in the assigned group, a degradation of 1.4 percent in performance would occur.

d. Models 18 and 19 are known as naive methods and require no calculations. In the model assignments in this study, several heuristics were decided upon as follows:

- (1) Do not assign long-term moving averages or global mean due to data storage considerations or high mean bias.
- (2) Assign either single, double, DLA formulations, and adaptive exponential smoothing using one or the combined exponential smoothing model but not both.

(3) Do not employ exponential smoothing with two distinct fixed smoothing constants due to the uncertainty of which to use in the future.

(4) Use the simple naive models as a baseline to measure performance due to ease of use. In forecasting literature performance is often measured by the Theil U Statistic, the ratio of the RMSE of the forecast model to the RMSE of no change extrapolation (Model 18).

(5) Use the simplest, most effective nonnaive seasonal model available, which in this study was the ARI with lag seasonal term. The ARI lag is, in effect, a regression using a naive monthly and the last year forecasts as independent variables.

The first of four sections of Table 11 indicates the mean bias (e.g., Theil's bias proportion averaged across all items) and the standard deviation about the mean bias for individual model assignment. Long-term averages such as model 1 - the Global mean and model 4 - the 36-month average exhibit high mean bias as can be observed here. These should be corrected for bias prior to their use.

The second section of Table 11 provides the mean bias (e.g., Theil's bias proportion averaged over assigned subclasses for each assigned model) and the standard deviation about that mean.

The third section of Table 11 reflects the performance distribution of the assigned group in deciles.

The fourth section of Table 11 indicates the future performance of the base model against the assigned set or the amount of error we accept using the base model in lieu of the assigned model group. The entire model assignment analysis is repeated for procurement cycle demand in Tables 12 through 15.

Optimal Linear Corrections and corrections for mean bias require the storage of extra data elements to perform forecast adjustments as do Autoregressive Harmonic Models. Nonetheless, based on the heuristics above, the assigned set appears optimal for perishable subsistence items.

Assignment of the forecast models may be made individually (e.g., simply replacement of present method by another or by a group).

Only methods that resulted in significant reduction in standard deviation of lead time and procurement cycle demand were accepted for assignment. If a model was unacceptably biased ( $U^M > .2$ ), it was rejected. However, in this case, a pre-correction for mean bias could be employed. This approach would result in even greater reductions in standard deviation of lead time and procurement cycle demand.

## 2. Construction of Model Groups for the Subsistence Commodity.

The solution of the model assignment problem requires a procedure to rank the competing models against the current method for a specified group of items. It

Table 11

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
LEAD TIME DEMAND - BIAS AND OVERALL  
PERFORMANCE OF GROUP ASSIGNMENT

| MODEL BIAS                             |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
|--|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|-----|-----|------|--|--|
|  | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   | 16   | 17   | 18   |     |     |      |  |  |
|  | 19   | 20   | 21   | 22   | 23   | 24   | 25   | 26   |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
|  | .245 | .059 | .126 | .182 | .186 | .091 | .058 | .041 | .032 | .026 | .042 | .010 | .005 | .046 | .016 | .012 | .028 | .013 |     |     |      |  |  |
|  | .083 | .010 | .067 | .060 | .067 | .056 | .063 | .058 |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
|  | .242 | .096 | .164 | .203 | .208 | .131 | .096 | .075 | .062 | .052 | .083 | .022 | .012 | .086 | .031 | .024 | .048 | .033 |     |     |      |  |  |
|  | .118 | .024 | .096 | .092 | .095 | .085 | .092 | .088 |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
| ASSIGNMENT BIAS                        |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
|  | 2    | 7    | 18   | 19   | 21   |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
|  | .046 | .045 | .054 | .043 | .065 |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
|  | .071 | .069 | .077 | .063 | .087 |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
| PERCENT REDUCTION IN BASE MODEL S.D.   |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
| MODEL                                  | 100  | 90   | 80   | 70   | 60   | 50   | 40   | 30   | 20   | 10   | 0    | -10  | -20  | -30  | -40  | -50  | -60  | -70  | -80 | -90 | -100 |  |  |
|  | 0    | 1    | 2    | 1    | 5    | 14   | 168  | 581  | 703  | 389  | 125  | 4    | 0    | 0    | 0    | 0    | 0    | 0    | 0   | 0   | 0    |  |  |
| AVERAGE BASE S.D./ASSIGNED S.D. =122.7 |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |     |     |      |  |  |
| MODEL                                  | 100  | 90   | 80   | 70   | 60   | 50   | 40   | 30   | 20   | 10   | 0    | -10  | -20  | -30  | -40  | -50  | -60  | -70  | -80 | -90 | -100 |  |  |
|  | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 3    | 124  | 342  | 499  | 466  | 306  | 157  | 54   | 21   | 7   | 3   | 11   |  |  |



MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
PROCUREMENT CYCLE DEMAND - ASSIGNMENT OCCURRENCE AND  
INDIVIDUAL ASSIGNMENT DISTRIBUTION MATRICES

1993 SERIES ACCEPTED

REDUCTION IN BASE RMSE

Table 12 (Continued)

[illegible]

Table 13

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
PROCUREMENT CYCLE DEMAND - INDIVIDUAL VS. BASE  
PERFORMANCE AND PERFORMANCE OF ASSIGNMENT  
ALLOCATION

## INDIVIDUAL MODEL V.S. BASE MODEL

|       | 1     | 2     | 3     | 4     | 5     | 6    | 7    | 8    | 9    | 10   | 11    | 12    | 13   | 14   | 15   | 16   | 17    | 18    | 19    | 20 |
|-------|-------|-------|-------|-------|-------|------|------|------|------|------|-------|-------|------|------|------|------|-------|-------|-------|----|
| 21    | 22    | 23    | 24    | 25    | 26    |      |      |      |      |      |       |       |      |      |      |      |       |       |       |    |
| 97.4  | 88.7  | 91.4  | 94.5  | 93.7  | 89.0  | 88.8 | 89.4 | 90.4 | 91.4 | 93.6 | 102.6 | 115.7 | 91.2 | 95.2 | 99.0 | 89.0 | 111.4 | 115.8 | 100.0 |    |
| 104.3 | 112.1 | 242.9 | 112.3 | 243.0 | 111.4 |      |      |      |      |      |       |       |      |      |      |      |       |       |       |    |
| 26.5  | 10.7  | 15.4  | 20.8  | 21.3  | 10.5  | 7.9  | 6.5  | 5.5  | 4.7  | 10.2 | 6.5   | 7.3   | 8.9  | 5.9  | 4.8  | 7.5  | 4.9   | 23.6  | .0    |    |
| 19.0  | 24.9  | 82.1  | 20.7  | 82.1  | 21.0  |      |      |      |      |      |       |       |      |      |      |      |       |       |       |    |
| .10   | 1.05  | .56   | .26   | .30   | 1.04  | 1.42 | 1.63 | 1.76 | 1.84 | .63  | -.39  | -2.16 | .99  | .81  | .20  | 1.48 | -2.34 | -.67  | .00   |    |
| -.22  | -.49  | -1.74 | -.60  | -1.74 | -.54  |      |      |      |      |      |       |       |      |      |      |      |       |       |       |    |

## REDUCTION IN BASE RMSE FOR ASSIGNED MODELS

| MODEL | 100 | 90 | 80 | 70 | 60 | 50 | 40 | 30  | 20  | 10  | 0   | -10 | -20 | -30 | -40 | -50 | -60 | -70 | -80 | -90 | -100 |
|-------|-----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 2:    | 0   | 0  | 0  | 0  | 0  | 0  | 1  | 16  | 300 | 518 | 97  | 5   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 7:    | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 1   | 22  | 355 | 403 | 86  | 6   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 18:   | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 0   | 0   | 0   | 6   | 27  | 1   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 19:   | 0   | 0  | 0  | 2  | 1  | 6  | 4  | 9   | 22  | 4   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
| 21:   | 0   | 0  | 0  | 0  | 0  | 1  | 4  | 6   | 23  | 24  | 30  | 13  | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |
|       | 0   | 0  | 2  | 1  | 7  | 9  | 32 | 367 | 901 | 536 | 131 | 7   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |

Table 14

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
PROCUREMENT CYCLE DEMAND - ASSIGNMENT CONTRIBUTION MATRIX

| ASSIGNMENT | CONTRIBUTION | 1    | 2   | 3    | 4    | 5   | 6   | 7   | 8    | 9    | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 |
|------------|--------------|------|-----|------|------|-----|-----|-----|------|------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 593        | 4.0          | 1.2  | 1.2 |      |      |     |     |     |      |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 937        | -2.8         | -1.3 | -3  | -1.3 |      |     |     |     |      |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 613        | 3.4          | 1.0  | 1.6 | .4   | 1.0  |     |     |     |      |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 589        | 3.8          | 1.1  | 1.4 | .3   | 1.5  | 1.1 |     |     |      |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 618        | 3.6          | 1.1  | 1.6 | .3   | 1.6  | 1.6 | 1.1 |     |      |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 641        | 1.6          | .5   | 1.3 | -.3  | 1.2  | 1.2 | 1.2 |     |      |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 7873       | -2.8         | -1.2 | .5  | 16.1 | .3   | .4  | .5  | 5   | -1.2 |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 8406       | 1.4          | .3   | 1.5 | -1.0 | 1.3  | 1.4 | 1.4 | .8  | .0   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 9388       | 2.1          | .4   | 1.6 | -.9  | 1.5  | 1.5 | 1.5 | .9  | .0   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 341        | 2.7          | .5   | 1.6 | -.9  | 1.5  | 1.6 | 1.6 | 1.0 | .0   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 145        | 3.2          | .2   | 1.4 | -1.1 | 1.3  | 1.3 | 1.4 | .7  | .7   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 59         | 3.9          | .1   | 1.3 | -1.2 | 1.2  | 1.2 | 1.2 | .6  | -1.0 |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 13         | 14           | 3.0  | .0  | 1.2  | -1.3 | 1.1 | 1.1 | 1.2 | .5   | -1.2 |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 222        | 2.7          | .3   | 1.5 | -.9  | 1.4  | 1.4 | 1.4 | .8  | .5   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 206        | 3.8          | .4   | 1.6 | -.9  | 1.4  | 1.5 | 1.5 | .9  | .4   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 151        | 4.2          | .3   | 1.5 | -1.0 | 1.4  | 1.4 | 1.4 | .8  | .6   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 492        | 2.8          | .7   | 1.7 | -.4  | 1.6  | 1.6 | 1.6 | 1.0 | .2   |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 34         | -8.4         | -.1  | 1.0 | -1.5 | .9   | 1.0 | 1.0 | .4  | -1.5 |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 48         | -10.6        | -.3  | .9  | -1.7 | .8   | .9  | .9  | .3  | -1.5 |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 137        | 3.6          | .2   | 1.4 | -1.1 | 1.3  | 1.4 | 1.4 | .8  | -.7  |      |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 101        | -5.2         | -.3  | .9  | -1.8 | .8   | .9  | .9  | .3  | -1.5 | .0   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 23         | 4.1          | .0   | 1.2 | -1.2 | 1.1  | 1.2 | 1.2 | .6  | -1.2 | .3   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 2          | 8.8          | .0   | 1.2 | -1.3 | 1.1  | 1.1 | 1.1 | .5  | -1.2 | .3   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 27         | 5.0          | .1   | 1.2 | -1.2 | 1.1  | 1.2 | 1.2 | .6  | -1.1 | .3   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 2          | 8.8          | .0   | 1.2 | -1.3 | 1.1  | 1.1 | 1.1 | .5  | -1.2 | .3   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |
| 25         | 3.8          | .0   | 1.2 | -1.2 | 1.1  | 1.2 | 1.2 | .6  | -1.2 | .3   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |

Table 15

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:  
PROCUREMENT CYCLE DEMAND - BIAS AND OVERALL  
PERFORMANCE OF GROUP ASSIGNMENT

## MODEL BIAS

| 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   | 16   | 17   | 18   |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 19   | 20   | 21   | 22   | 23   | 24   | 25   | 26   |      |      |      |      |      |      |      |      |      |      |
| .190 | .050 | .099 | .141 | .141 | .072 | .048 | .036 | .029 | .025 | .037 | .010 | .006 | .037 | .015 | .013 | .029 | .009 |
| .052 | .013 | .050 | .053 | .844 | .053 | .844 | .051 |      |      |      |      |      |      |      |      |      |      |
| .210 | .084 | .138 | .172 | .173 | .109 | .082 | .067 | .056 | .049 | .071 | .020 | .012 | .071 | .031 | .027 | .051 | .020 |
| .080 | .028 | .078 | .082 | .103 | .079 | .103 | .080 |      |      |      |      |      |      |      |      |      |      |

## ASSIGNMENT BIAS

| 2    | 7    | 18   | 19   | 21   |
|------|------|------|------|------|
| .038 | .046 | .053 | .040 | .055 |
| .058 | .074 | .063 | .063 | .076 |

## PERCENT REDUCTION IN BASE MODEL S.D.

| MODEL | 100 | 90 | 80 | 70 | 60 | 50 | 40 | 30 | 20  | 10  | 0   | -10 | -20 | -30 | -40 | -50 | -60 | -70 | -80 | -90 | -100 |
|-------|-----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
|       | 0   | 0  | 0  | 2  | 1  | 7  | 9  | 32 | 367 | 901 | 536 | 131 | 7   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0    |

## AVERAGE BASE S.D./ASSIGNED S.D. = 117.1

| MODEL | 100 | 90 | 80 | 70 | 60 | 50 | 40 | 30 | 20 | 10 | 0   | -10 | -20 | -30 | -40 | -50 | -60 | -70 | -80 | -90 | -100 |
|-------|-----|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
|       | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 6  | 131 | 452 | 706 | 459 | 164 | 47  | 8   | 1   | 5   | 1   | 13   |

- is necessary to test individual model assignments across the entire subsistence commodity and to test groups of competing models and their interactions. The authors designed software to construct a group of models for any set of subsistence items. The model assignment analysis technique will be used to construct various model groups for perishable and semiperishable subsistence, respectively.

Due to the large number of models to be evaluated, initial screening was necessary to develop a final model test set from which to select a model group. Fourteen model test sets are described in Appendix N. There was only a 3% to 5% variation in performance (RMSE reduction) among the model test sets when all models were assigned. Model test set 13 resulted in the greatest reduction in RMSE. Model test set 13 was then adjusted to determine if improvement could be achieved by the addition of exponential smoothing techniques. The resultant test set contains 26 models including model test set 13 (the harmonic models were dropped out of Model Test Set 13 as they provided little or no additional improvement), single, double, and adaptive exponential smoothing and the COMBINED model. This test set is used to develop model groups for assignment to subsistence commodity and is referenced in the model assignment reports as "MODELS ON FILE".

The construction of the model groups for the perishable and semiperishable item classes from individual to final group will now be described. (Assignment of the forecast models may be made individually (e.g., simply replace the present method by another) or as a group.

Using a model assignment analysis report, the performance statistics on the five best individuals models for perishable and semiperishable subsistence are derived. These performance statistics include mean reduction in RMSE, standard deviation about the mean reduction and the mean bias. Table 16 provides these performance statistics for the five best individual models.

Table 16

BEST INDIVIDUAL FORECAST PERFORMANCES FOR THE SUBSISTENCE COMMODITY

## Subsistence Category

| <u>Perishable</u>       |                                   |                |                      | <u>SemiPerishable</u> |                                   |                |                      |
|-------------------------|-----------------------------------|----------------|----------------------|-----------------------|-----------------------------------|----------------|----------------------|
| <u>Lead Time Demand</u> |                                   |                |                      |                       |                                   |                |                      |
| <u>Model</u>            | <u>Mean Reduction<br/>in RMSE</u> | <u>Std Dev</u> | <u>Mean<br/>Bias</u> | <u>Model</u>          | <u>Mean Reduction<br/>in RMSE</u> | <u>Std Dev</u> | <u>Mean<br/>Bias</u> |
| SES(.15)                | 13.3                              | 12.0           | .058                 | COMBINED              | 8.2                               | 9.6            | .056                 |
| SES(.20)                | 13.1                              | 10.0           | .041                 | SES(.15)              | 5.6                               | 10.9           | .103                 |
| COMBINED                | 12.7                              | 10.4           | .028                 | 12 Mo Avg             | 5.2                               | 14.2           | .100                 |
| SES(.25)                | 12.4                              | 8.6            | .032                 | SES(.20)              | 4.2                               | 7.3            | .074                 |
| 12 Mo Avg               | 12.0                              | 15.7           | .059                 | SES(.10)              | 3.0                               | 20.2           | .164                 |

| <u>Procurement Cycle Demand</u> |                                   |                |                      |              |                                   |                |                      |
|---------------------------------|-----------------------------------|----------------|----------------------|--------------|-----------------------------------|----------------|----------------------|
| <u>Model</u>                    | <u>Mean Reduction<br/>in RMSE</u> | <u>Std Dev</u> | <u>Mean<br/>Bias</u> | <u>Model</u> | <u>Mean Reduction<br/>in RMSE</u> | <u>Std Dev</u> | <u>Mean<br/>Bias</u> |
| 12 Mo Avg                       | 11.3                              | 10.7           | .050                 | COMBINED     | 5.8                               | 7.6            | .064                 |
| SES(.15)                        | 11.2                              | 7.9            | .048                 | SES(.15)     | 3.7                               | 8.1            | .098                 |
| COMBINED                        | 11.0                              | 7.5            | .029                 | 12 Mo Avg    | 3.0                               | 9.9            | .095                 |
| SES(.10)                        | 11.0                              | 10.5           | .072                 | SES(.10)     | 2.6                               | 13.8           | .140                 |
| SES(.20)                        | 10.6                              | 6.5            | .036                 | SES(.20)     | 1.6                               | 5.6            | .078                 |

Figure 3 depicts the distribution of performance for the best individual model assignment, SES(.15), for Perishable Subsistence. Note that while this method is often not the best for individual series, it is a solid performer that rarely performs poorly. On the average, in terms of reduced RMSE related to present DLA methods, it is the best of the models tested for perishable items.

Figure 4 provides the distribution of performance for the best individual model assignment for semiperishable subsistence, COMBINED.

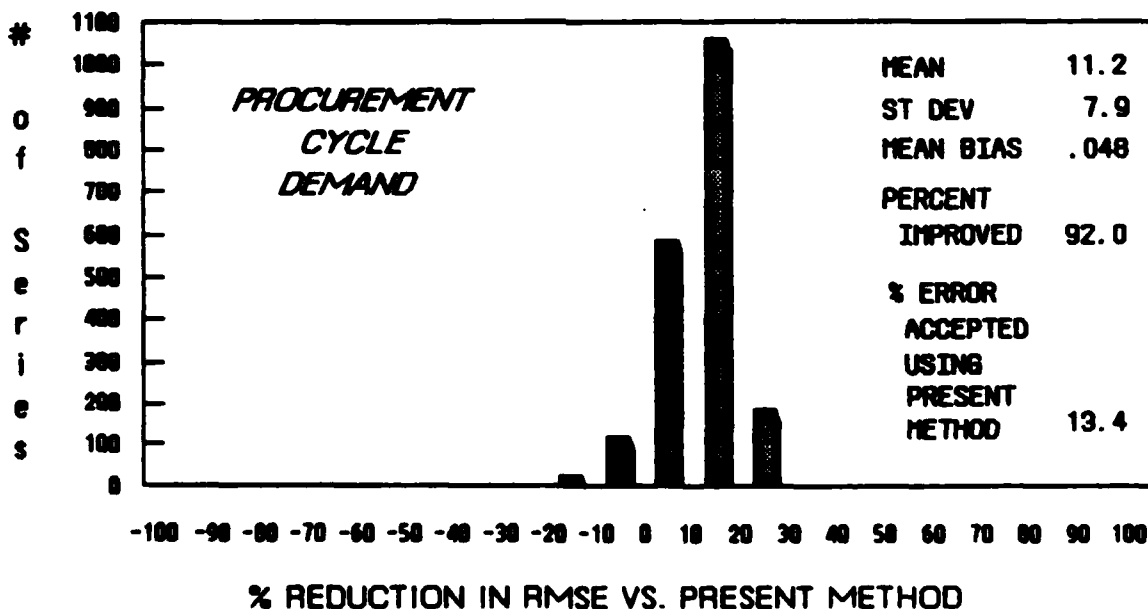
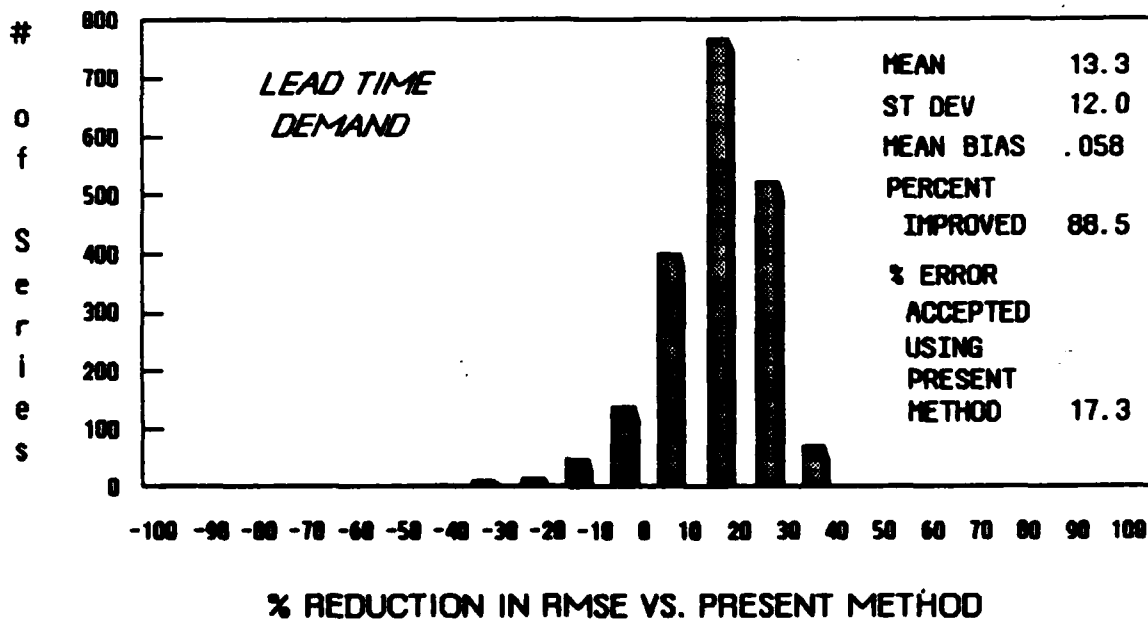
The best individual model provides the greatest improvement in forecast accuracy. The addition of other models results in marginally decreasing improvements in forecast performance.

The initial model in the recommended group is the best individual model. The next consideration was to include the naive models. The naive models, LAST LT/PC, represents no change forecasts from the last predictive period's actual demand. The naive model, LAST YEAR, represents no change forecasts from the actual demand last year during the same period.

The naive models serve as benchmarks in a forecasting system for the evaluation of trends and seasonal demand patterns. The best individual and two naive models are designated as the elementary model group.

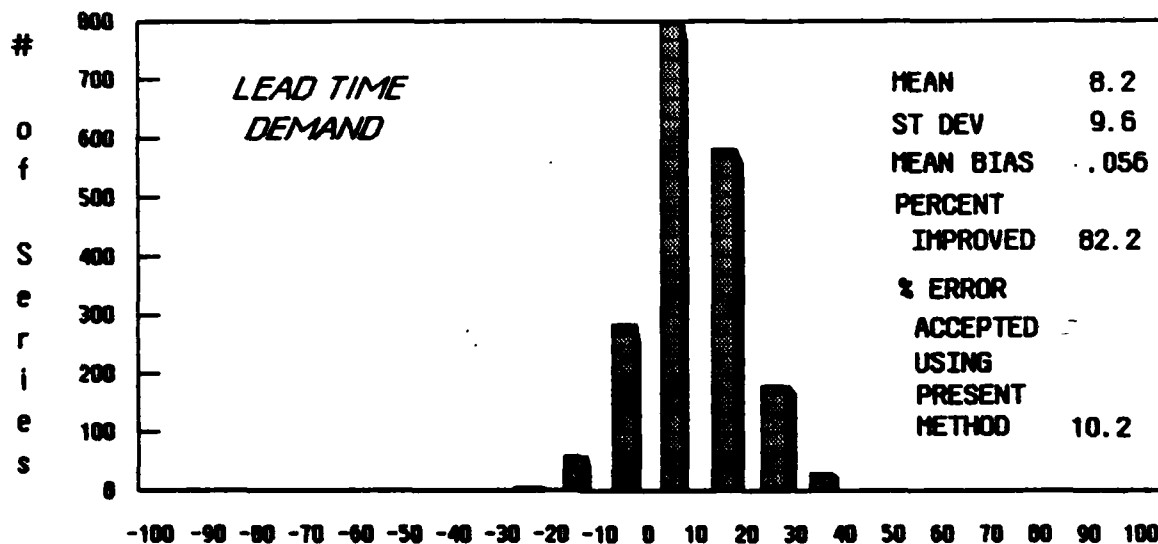
Appendix D contains the model assignment analyses for the elementary model groups. Table 17 demonstrates the comparative performance of the elementary model group and the best individual model. The Percent Improved columns in Table 17 refers to the percentage of demand series that experienced reduced RMSE over the present DLA forecast RMSE.

**FIGURE 3**  
**PERFORMANCE DISTRIBUTION OF**  
**BEST INDIVIDUAL FORECAST MODEL – SES (.15)**  
**PERISHABLE SUBSISTENCE**

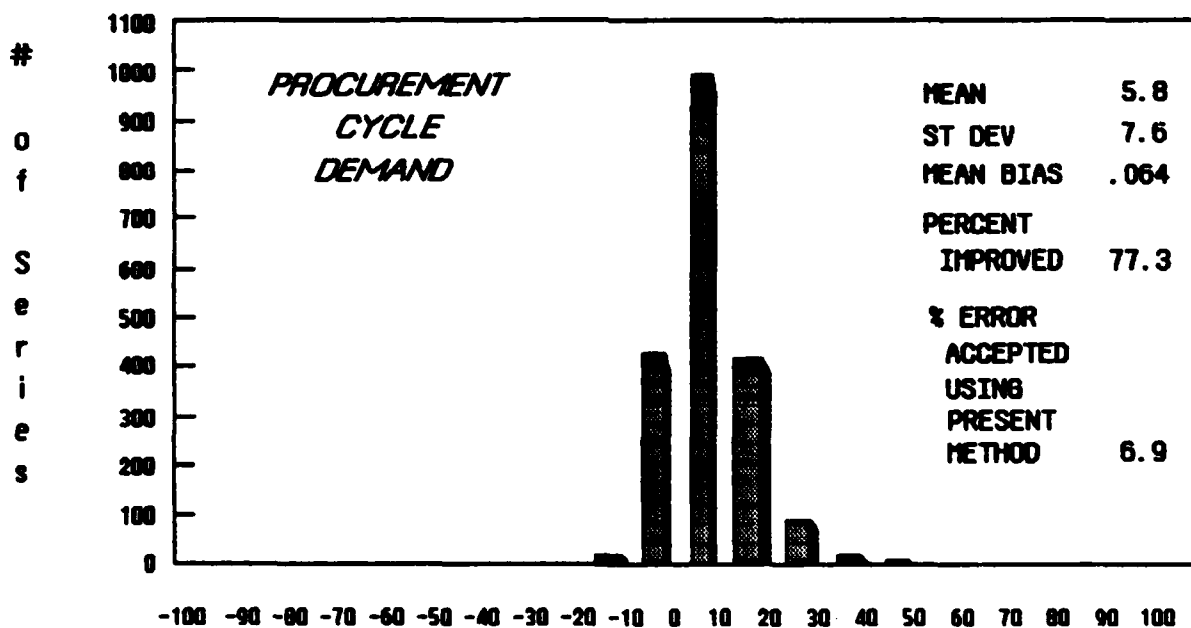




**FIGURE 4**  
**PERFORMANCE DISTRIBUTION OF**  
**BEST INDIVIDUAL FORECAST MODEL — COMBINED**  
**SEMI-PERISHABLE SUBSISTENCE**



**% REDUCTION IN RMSE VS. PRESENT METHOD**



**% REDUCTION IN RMSE VS. PRESENT METHOD**

Table 17

COMPARATIVE PERFORMANCE OF BEST INDIVIDUAL AND  
ELEMENTARY GROUPS OF FORECAST MODELS

| Subsistence Category            |                                   |                            |                       |                                   |                            |                      |
|---------------------------------|-----------------------------------|----------------------------|-----------------------|-----------------------------------|----------------------------|----------------------|
| <u>Perishable</u>               |                                   |                            | <u>SemiPerishable</u> |                                   |                            |                      |
| <u>Lead Time Demand</u>         |                                   |                            |                       |                                   |                            |                      |
| <u>Model</u>                    | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u>  | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u> |
| Best                            |                                   |                            |                       |                                   |                            |                      |
| Individual                      | 13.3                              | 88.5                       | .058                  | 8.2                               | 82.2                       | .056                 |
| Elementary                      |                                   |                            |                       |                                   |                            |                      |
| Group                           | 15.4                              | 92.0                       | .049                  | 10.1                              | 84.7                       | .063                 |
| <u>Procurement Cycle Demand</u> |                                   |                            |                       |                                   |                            |                      |
| <u>Model</u>                    | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u>  | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u> |
| Best                            |                                   |                            |                       |                                   |                            |                      |
| Individual*                     | 11.3                              | 92.0                       | .048                  | 5.8                               | 77.3                       | .064                 |
| Elementary                      |                                   |                            |                       |                                   |                            |                      |
| Group                           | 12.0                              | 92.4                       | .045                  | 6.6                               | 79.1                       | .064                 |

\* 12-MO AVG was slightly better (.1 percent) than SES(.15) for procurement cycle demand. However, in the interest of parsimony, SES(.15) is chosen as best individual model since it achieved less dispersion of performance.

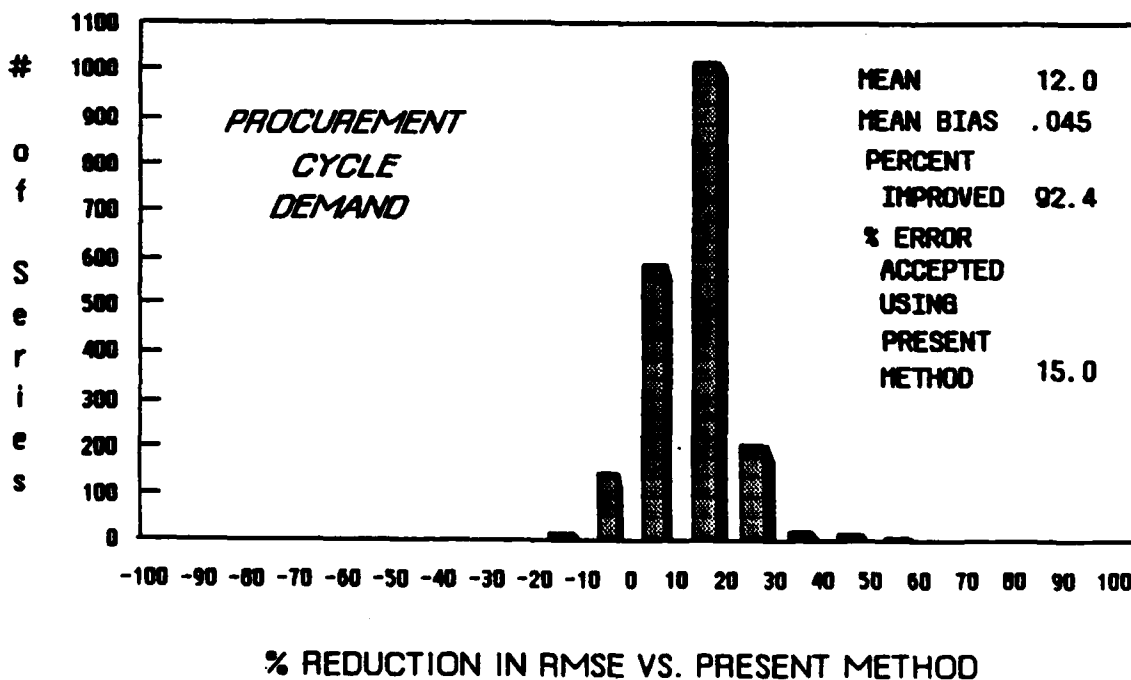
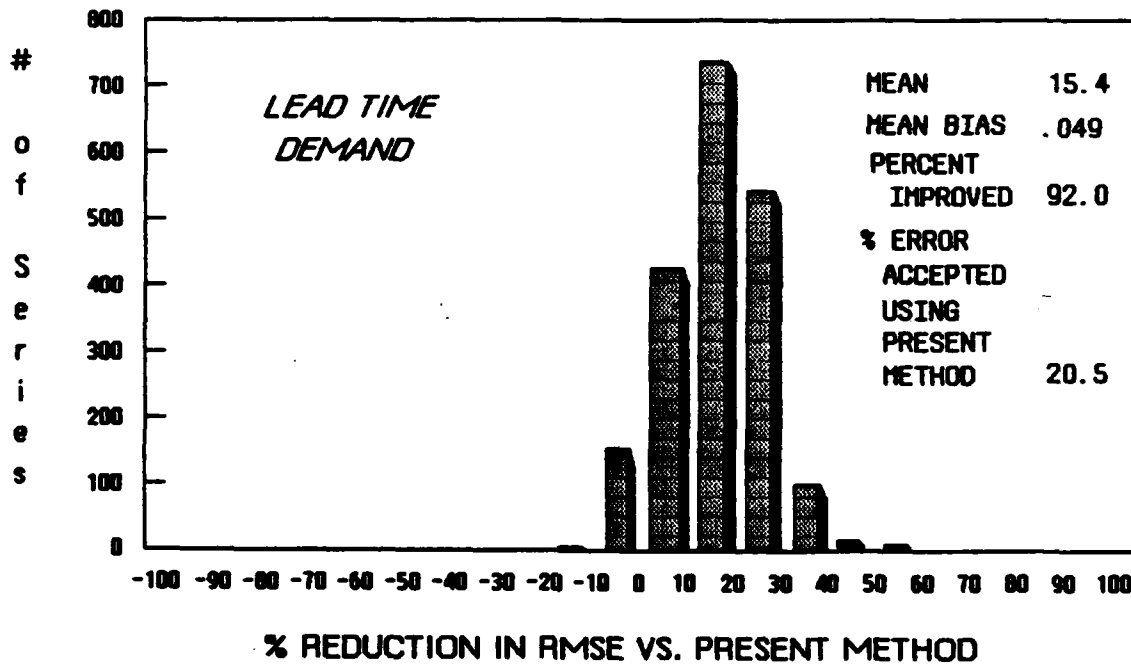
Figures 5 and 6 depict the performance distributions of the elementary model group assignments, for Perishable and Semiperishable Subsistence, respectively.

Examination of the model assignment analyses in Appendix D indicate that additional improvement exceeding a 1 percent reduction in RMSE can be achieved. However, the only model meeting the constraints of the heuristics in Section IIIF1 is the 12-MO AVG. For example, for perishable subsistence, model 1 - GLOBAL MEAN and model 3 - 24-MO AVG, are eliminated due to high mean bias and data storage requirements and SES(.05) is eliminated due to borderline high mean bias and the fact that model 7 - SES(.15) is already assigned. The same rationale holds for the semiperishable model assignment analysis.

Table 18 presents the comparative performance of the group when the 12-MO AVG is added. This group shall be designated the secondary model group.

FIGURE 5

PERFORMANCE DISTRIBUTION  
OF THE ELEMENTARY MODEL GROUP—  
PERISHABLE SUBSISTENCE



**FIGURE 6**  
**PERFORMANCE DISTRIBUTION OF THE**  
**ELEMENTARY MODEL GROUP –**  
**SEMIPERISHABLE SUBSISTENCE**

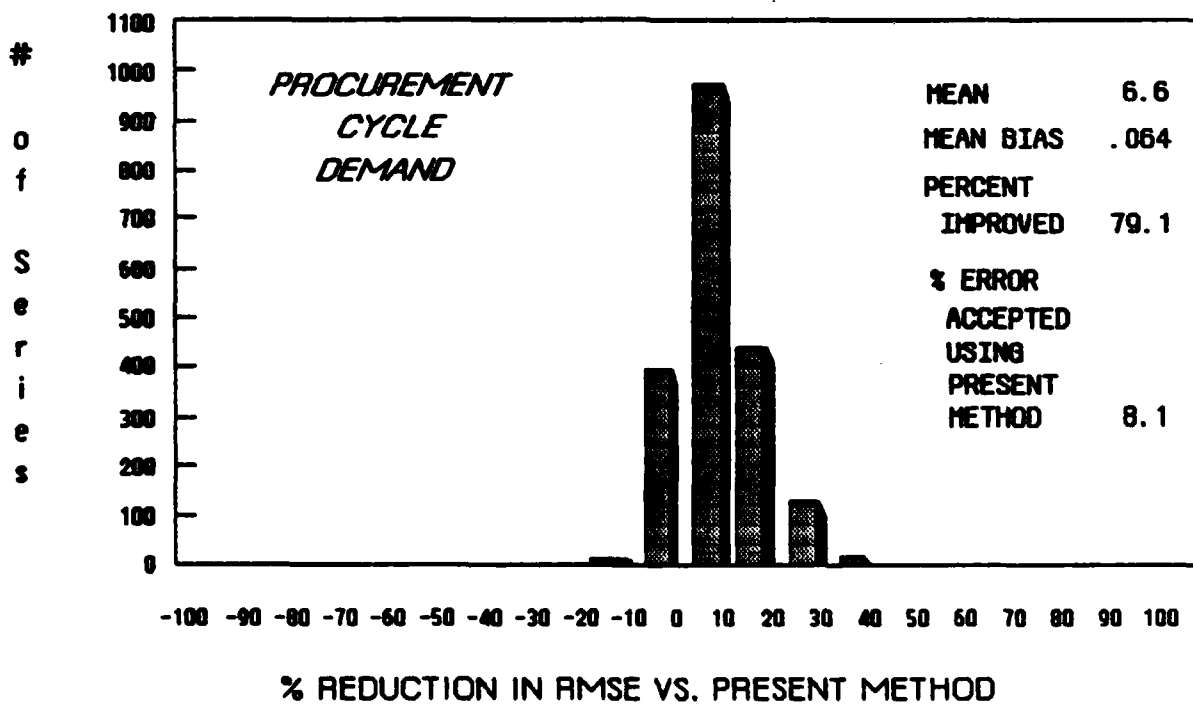
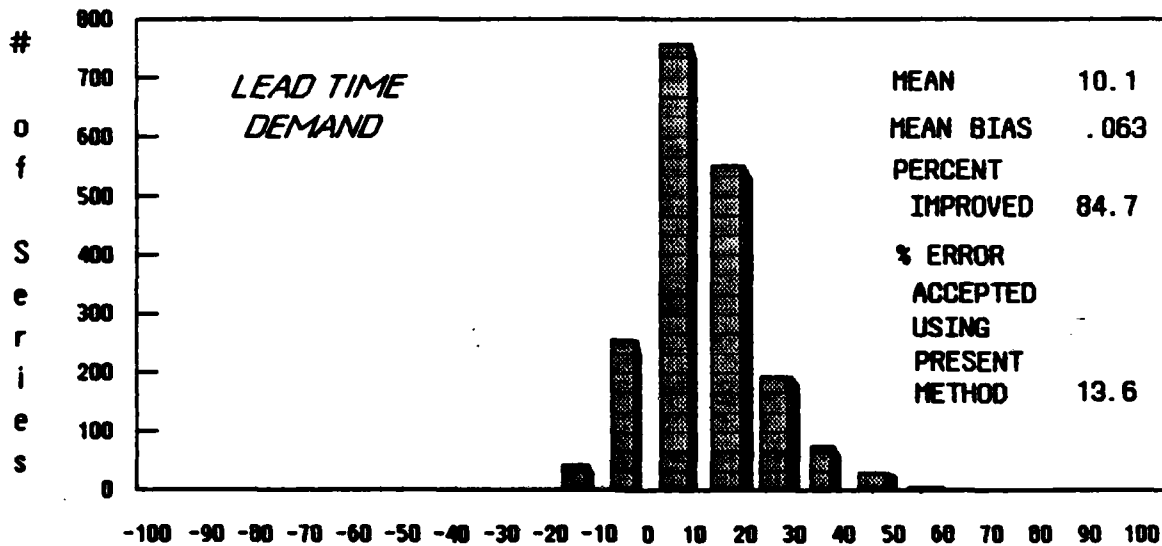


Table 18

COMPARATIVE PERFORMANCE OF BEST INDIVIDUAL,  
ELEMENTARY, AND SECONDARY GROUPS OF FORECAST MODELS

| Subsistence Category            |                                   |                            |                       |                                   |                            |                      |
|---------------------------------|-----------------------------------|----------------------------|-----------------------|-----------------------------------|----------------------------|----------------------|
| <u>Perishable</u>               |                                   |                            | <u>SemiPerishable</u> |                                   |                            |                      |
| <u>Lead Time Demand</u>         |                                   |                            |                       |                                   |                            |                      |
| <u>Model</u>                    | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u>  | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u> |
| Best                            |                                   |                            |                       |                                   |                            |                      |
| Individual                      | 13.3                              | 88.5                       | .058                  | 8.2                               | 82.2                       | .056                 |
| Elementary                      |                                   |                            |                       |                                   |                            |                      |
| Group                           | 15.4                              | 92.0                       | .049                  | 10.1                              | 84.7                       | .063                 |
| Secondary                       |                                   |                            |                       |                                   |                            |                      |
| Group                           | 16.4                              | 92.2                       | .050                  | 11.6                              | 88.2                       | .071                 |
| <u>Procurement Cycle Demand</u> |                                   |                            |                       |                                   |                            |                      |
| <u>Model</u>                    | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u>  | <u>Mean Reduction<br/>in RMSE</u> | <u>Percent<br/>Imprvd.</u> | <u>Mean<br/>Bias</u> |
| Best                            |                                   |                            |                       |                                   |                            |                      |
| Individual                      | 11.3                              | 92.0                       | .048                  | 5.8                               | 77.3                       | .064                 |
| Elementary                      |                                   |                            |                       |                                   |                            |                      |
| Group                           | 12.0                              | 92.4                       | .045                  | 6.6                               | 79.1                       | .064                 |
| Secondary                       |                                   |                            |                       |                                   |                            |                      |
| Group                           | 13.2                              | 92.7                       | .046                  | 7.8                               | 84.9                       | .074                 |

Figures 7 and 8 depict the performance distributions of the secondary model group assignments, for Perishable and SemiPerishable Subsistence, respectively.

Appendix E contains the model assignment analyses for the secondary model group.

Examination of the model assignment analyses in Appendix E indicate that improvements in forecast accuracy exceeding .75 percent could be achieved, within the constraints of the heuristics in Section IIIF1, only by the addition of an autoregressive seasonal model. Model 25 - SAR1 Lag and Model 21 - AR1 Lag are candidates. Model 25 performs slightly better than Model 21 for lead time demand while Model 21 performs even more better than Model 25 for procurement cycle demand. Due to this fact and in the interest of parsimony, Model 21 was added to the secondary group of models in Appendix E. At this point, we have reached the point of diminishing returns within the constraints of the heuristics in Section IIIF1. The groups, derived from the addition of the AR1 Lag Seasonal Model, to the Secondary groups, will be designated as the Final Model Groups.

Table 19 depicts the performance of the final model groups for the Subsistence Commodity.

FIGURE 7

PERFORMANCE DISTRIBUTION  
OF THE SECONDARY MODEL GROUP—  
PERISHABLE SUBSISTENCE

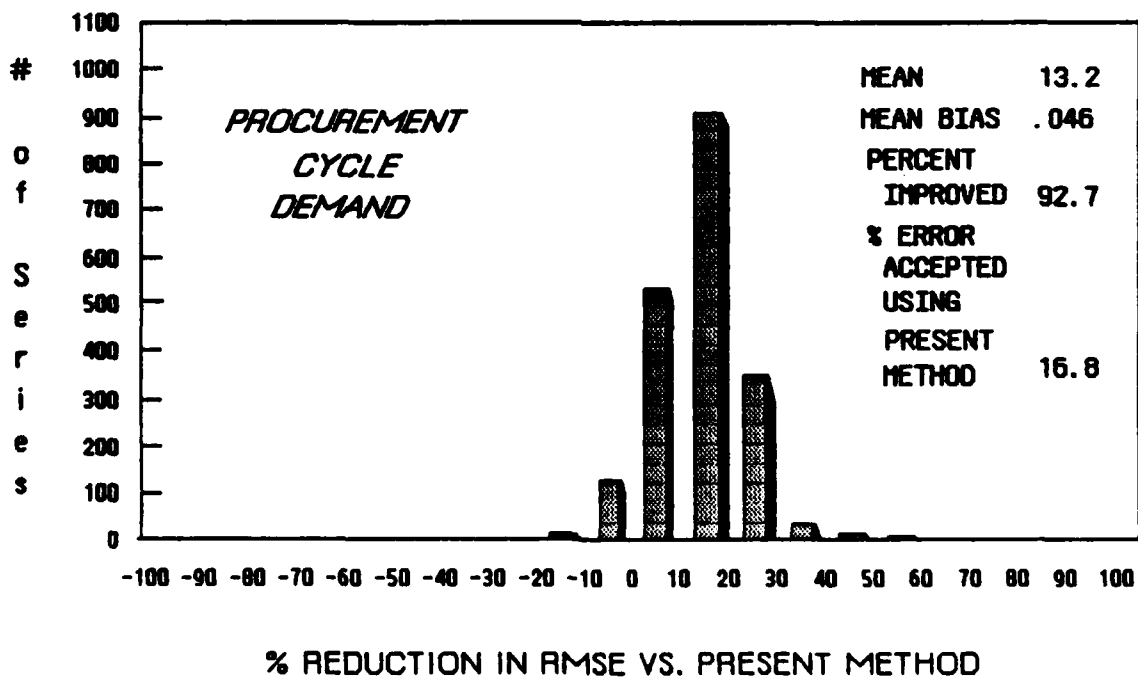
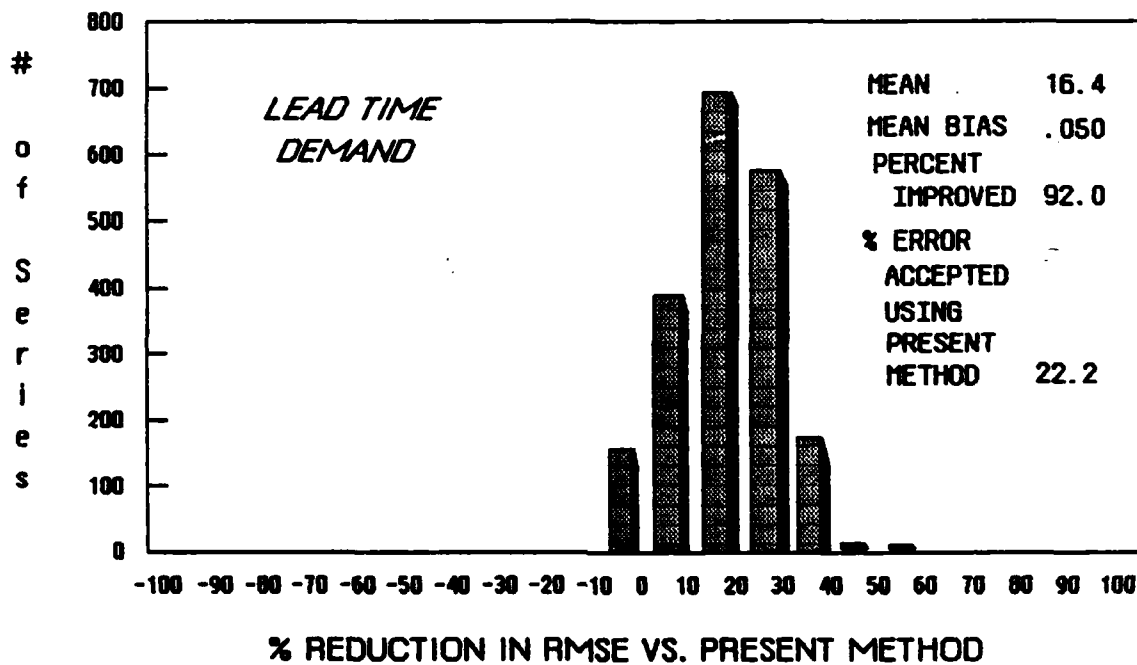
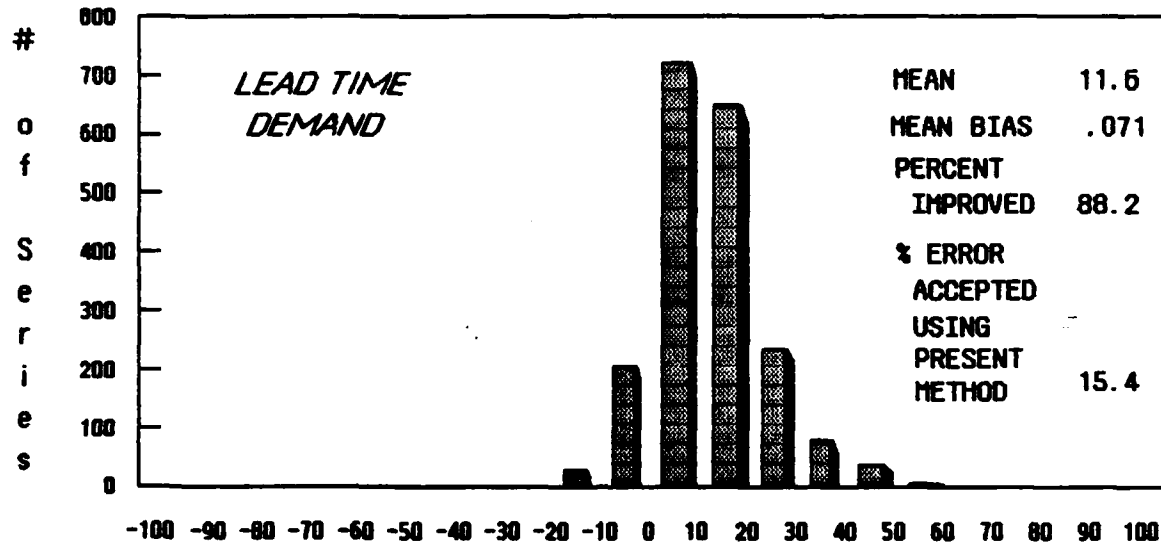
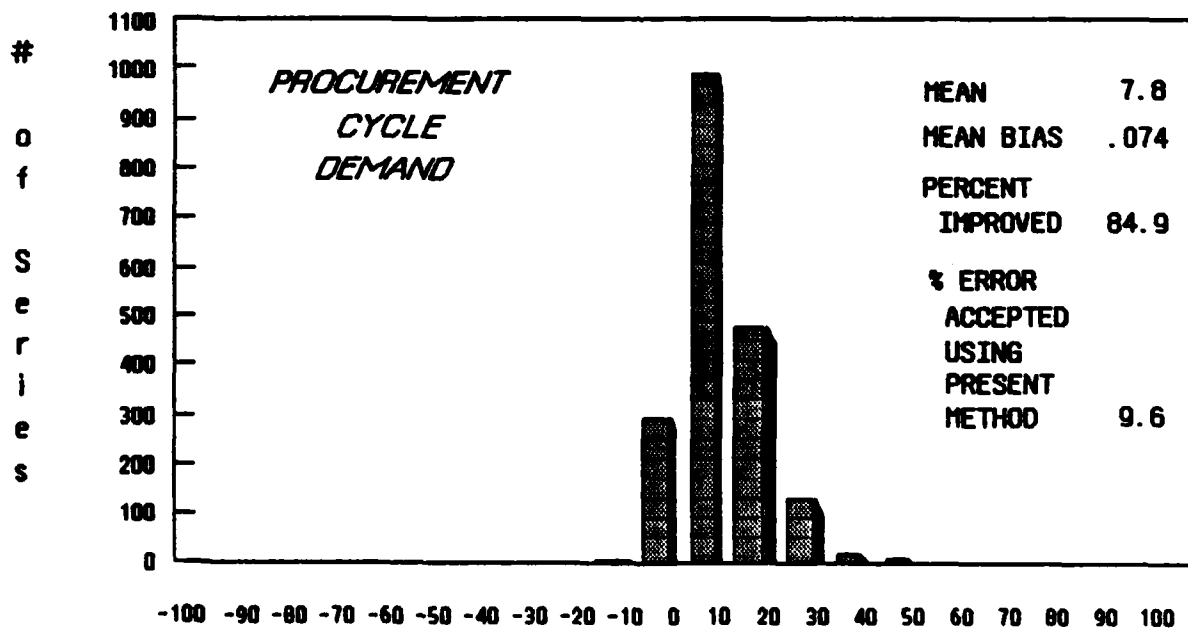


FIGURE 8  
PERFORMANCE DISTRIBUTION OF THE  
SECONDARY MODEL GROUP -  
SEMIPERISHABLE SUBSISTENCE



% REDUCTION IN RMSE VS. PRESENT METHOD



% REDUCTION IN RMSE VS. PRESENT METHOD

Table 19

PERFORMANCE OF THE FINAL MODEL GROUPS  
FOR THE SUBSISTENCE COMMODITY

| Subsistence Category                         |  |  |
|--|--|--|
| Group  | <u>Perishable</u>                                      | <u>Semiperishable</u>                                  |
|  | Lead Time Demand                                       |  |
|  | 12-MO AVG, SES(.15),<br>Last LT, Last Year,<br>ARL Lag | 12-MO AVG, COMBINED,<br>Last LT, Last Year,<br>ARL Lag |
| Mean Reduction<br>in RMSE                    | 16.8   | 12.4   |
| Percent Improved                             | 93.5   | 90.4   |
| Mean Bias                                    | .047   | .068   |
| % Error Accepted<br>Using Present<br>Methods | 22.7   | 16.5   |
| Procurement Cycle Demand                     |  |  |
| Group  | 12-MO AVG, SES(.15),<br>Last PC, Last Year,<br>ARL Lag | 12-MO AVG, COMBINED,<br>Last PC, Last Year,<br>ARL Lag |
|  | ARL Lag  | ARL Lag  |
| Mean Reduction<br>in RMSE                    | 13.4   | 8.3  |
| Percent Improved                             | 93.1   | 86.1   |
| Mean Bias                                    | .043   | .065   |
| % Error Accepted<br>Using Present<br>Methods | 17.1   | 10.2   |

Figures 9 and 10 depict the performance distributions of the final model group assignments, for Perishable and Semiperishable Subsistence, respectively.

Figure 11 provides a comparison of the performance of the best individual, elementary, secondary and final model groups for perishable and semiperishable subsistence, respectively.

### 3. Model Assignments and Item Characteristics

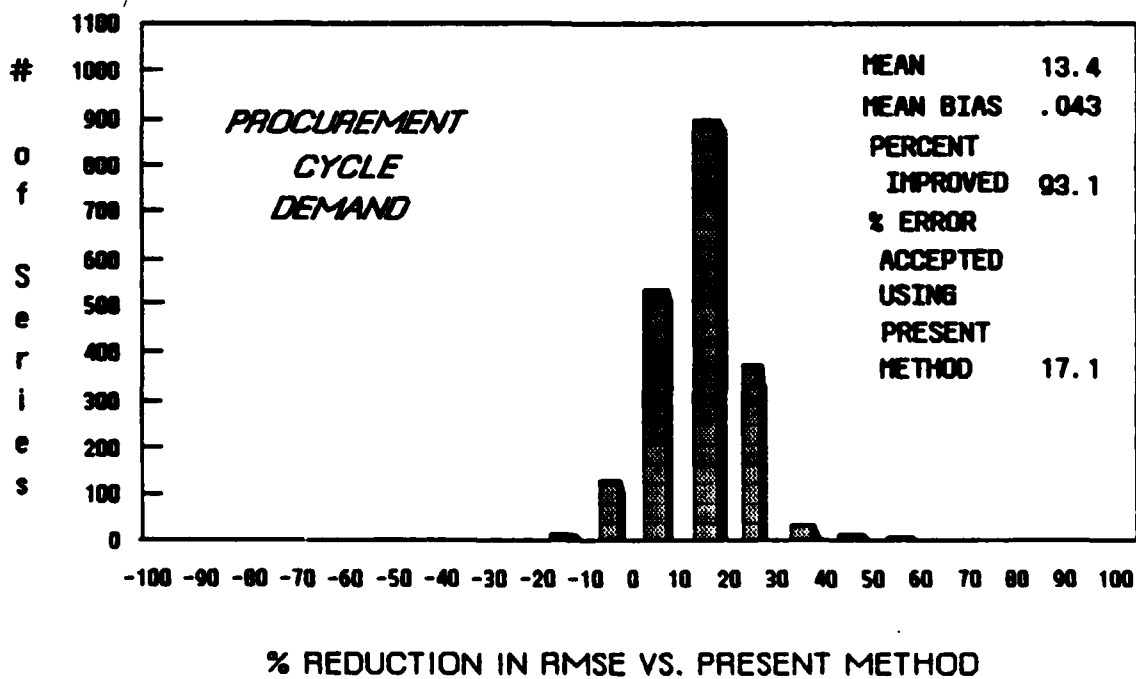
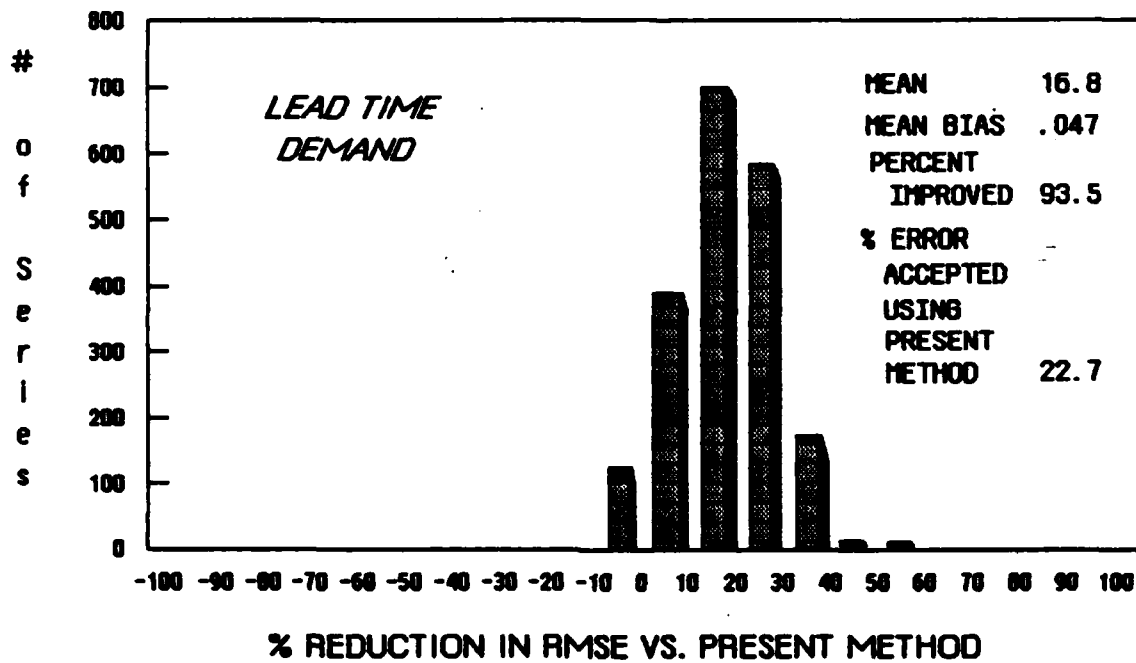
The assignment of the final model group differed by item characteristic. This section of the report highlights variations in the assignment and performance of the final model group by the following characteristics:

- (1) Item Category - Troop Issue vs. Brand Name
- (2) Lead Time and Procurement Cycle Duration

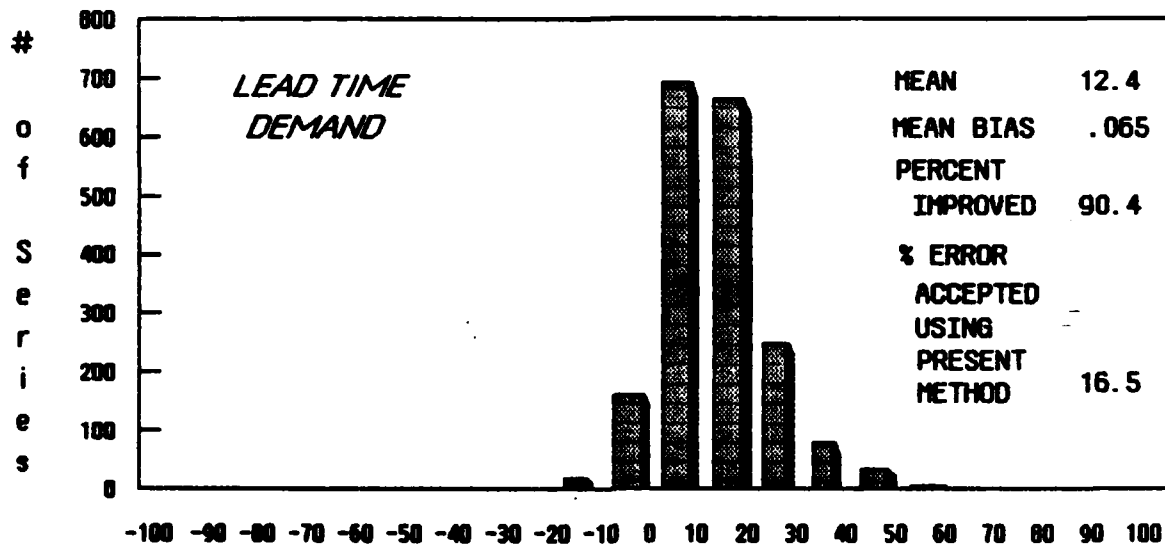


FIGURE 9

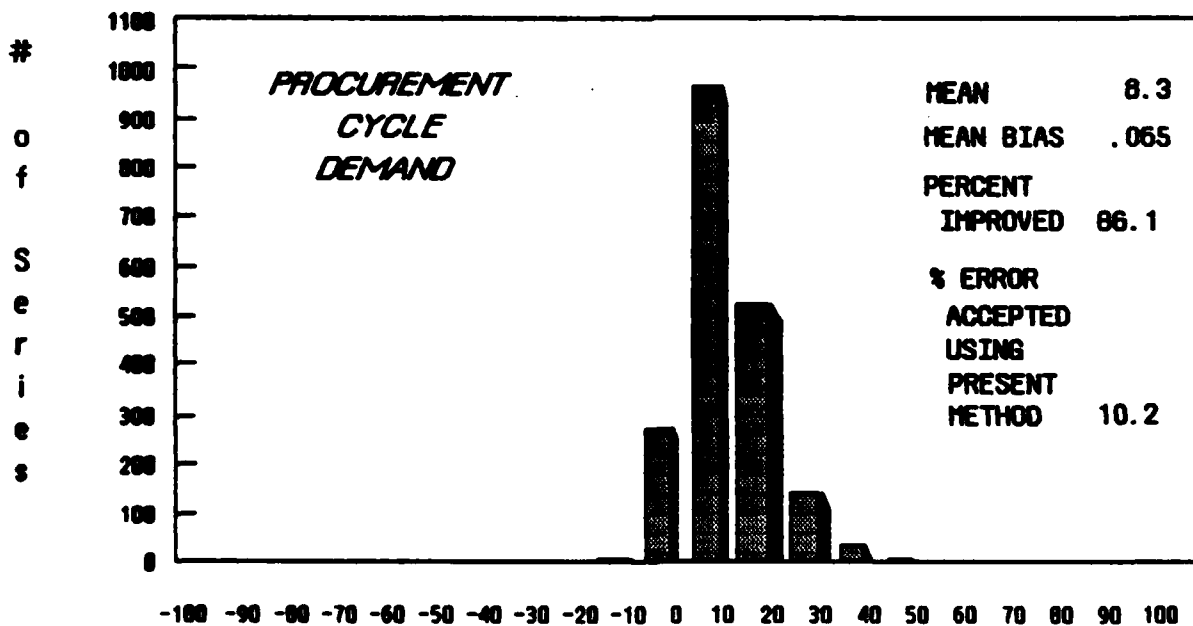
PERFORMANCE DISTRIBUTION  
OF THE FINAL MODEL GROUP—  
PERISHABLE SUBSISTENCE



**FIGURE 10**  
**PERFORMANCE DISTRIBUTION OF THE**  
**FINAL MODEL GROUP -**  
**SEMIPERISHABLE SUBSISTENCE**

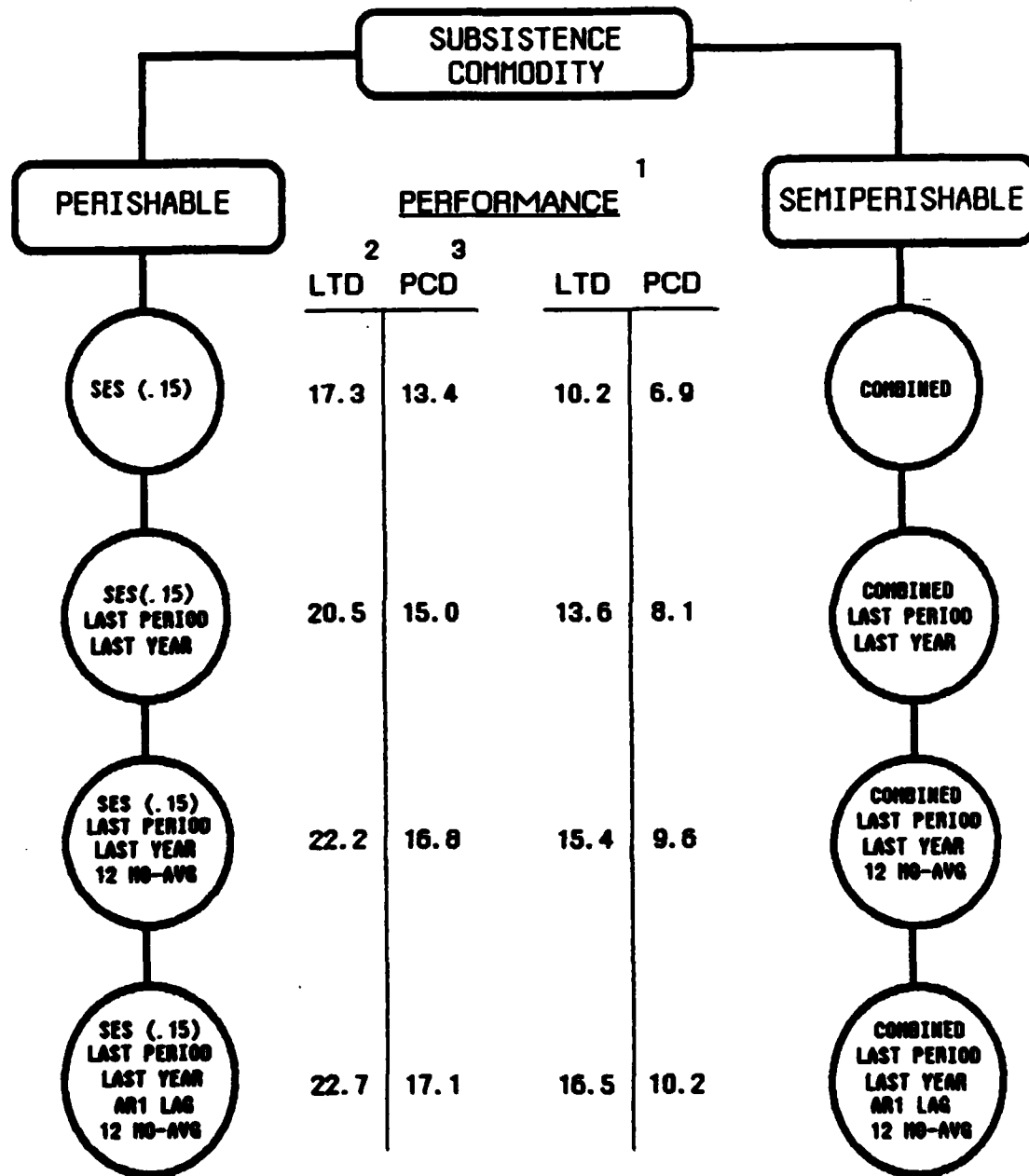


**% REDUCTION IN RMSE VS. PRESENT METHOD**



**% REDUCTION IN RMSE VS. PRESENT METHOD**

**FIGURE 11**  
**COMPARISON OF FORECAST MODEL GROUP PERFORMANCE**  
**FOR THE SUBSISTENCE COMMODITY**



<sup>1</sup> % ERROR ACCEPTED PRESENTLY IN LIEU OF USING NEW METHODS

<sup>2</sup> LEAD TIME DEMAND

<sup>3</sup> PROCUREMENT CYCLE DEMAND

Variations in Model assignment by item characteristics are important in designing decision rules for model assignments to new items.

Tables 20 and 21 provide the frequency of occurrence of the recommended model group assignments by item category (troop issue vs brand name) for perishable and semiperishable subsistence, respectively. The final Model Group is split into Nonseasonal and Seasonal components for comparative purposes.

Table 20

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENT BY  
ITEM CATEGORY: PERISHABLE SUBSISTENCE

| <u>Lead Time Demand</u>         |                                     |                               |                         |
|---------------------------------|-------------------------------------|-------------------------------|-------------------------|
| <u>ITEM CATEGORY</u>            | <u>% of Total Perishable Sample</u> | <u>Mean Reduction in RMSE</u> | <u>Percent Improved</u> |
| <u>TROOP ISSUE</u>              |                                     |                               |                         |
| Nonseasonal                     | 64.2                                | 17.4                          | 95.9                    |
| Seasonal                        | 4.9                                 | 23.5                          | 94.8                    |
| Total                           | 69.1                                | 17.9                          | 95.5                    |
| <u>BRAND NAME</u>               |                                     |                               |                         |
| Nonseasonal                     | 25.4                                | 13.7                          | 88.5                    |
| Seasonal                        | 5.5                                 | 17.5                          | 91.7                    |
| Total                           | 30.9                                | 14.4                          | 89.1                    |
| <u>Procurement Cycle Demand</u> |                                     |                               |                         |
| <u>TROOP ISSUE</u>              |                                     |                               |                         |
| Nonseasonal                     | 65.3                                | 12.2                          | 92.7                    |
| Seasonal                        | 3.8                                 | 19.9                          | 85.7                    |
| Total                           | 69.1                                | 12.5                          | 92.3                    |
| <u>BRAND NAME</u>               |                                     |                               |                         |
| Nonseasonal                     | 27.3                                | 13.0                          | 94.5                    |
| Seasonal                        | 3.6                                 | 21.5                          | 97.2                    |
| Total                           | 30.9                                | 15.5                          | 94.8                    |

Table 21

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENT BY  
ITEM CATEGORY: SEMIPERISHABLE SUBSISTENCE

| <u>Lead Time Demand</u>         |                                     |                               |                         |
|---------------------------------|-------------------------------------|-------------------------------|-------------------------|
| <u>ITEM CATEGORY</u>            | <u>% of Total Perishable Sample</u> | <u>Mean Reduction in RMSE</u> | <u>Percent Improved</u> |
| <u>TROOP ISSUE</u>              |                                     |                               |                         |
| Nonseasonal                     | 49.8                                | 13.6                          | 95.7                    |
| Seasonal                        | 7.8                                 | 31.4                          | 100.0                   |
| Total                           | 57.6                                | 16.0                          | 96.3                    |
| <u>BRAND NAME</u>               |                                     |                               |                         |
| Nonseasonal                     | 31.9                                | 5.7                           | 79.1                    |
| Seasonal                        | 10.5                                | 13.2                          | 92.1                    |
| Total                           | 42.4                                | 7.5                           | 82.3                    |
| <u>Procurement Cycle Demand</u> |                                     |                               |                         |
| <u>TROOP ISSUE</u>              |                                     |                               |                         |
| Nonseasonal                     | 51.4                                | 10.6                          | 92.6                    |
| Seasonal                        | 6.2                                 | 16.8                          | 98.3                    |
| Total                           | 57.6                                | 11.3                          | 93.3                    |
| <u>BRAND NAME</u>               |                                     |                               |                         |
| Nonseasonal                     | 36.8                                | 3.5                           | 74.1                    |
| Seasonal                        | 5.6                                 | 9.7                           | 90.8                    |
| Total                           | 42.4                                | 4.3                           | 76.3                    |

Tables 20 and 21 indicate that Seasonal Models generally provide from 27 to 277% better forecasts than their nonseasonal counterparts on their assigned subclasses. This is not surprising as the present DLA forecast does not consider seasonal patterns. Also, forecast performance for the troop issue category exceeded that for brand name, with the exception of procurement cycle demand for perishable items. Seasonality is most prevalent in the Semiperishable brand name category (25%) yet rare in the Perishable troop issue area (7%).

Tables 22 and 23 indicate that seasonality is most prevalent at lead times of four months for the perishable class and five months for the semiperishable class.

Figure 12 highlights the distribution assignments of the seasonal component of the final model group for the subsistence commodity.

Table 22

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENTS BY LEADTIME DURATION

Perishable Subsistence

| <u>LT Duration</u> | <u>% of Total<br/>Perishable Sample</u> | <u>% of Items Assigned to Model Type<br/>Nonseasonal</u> | <u>Seasonal</u> |
|--------------------|---|--|-----------------|
| 2                  | 8.2                                     | 94   | 6               |
| 3                  | 58.9                                    | 92   | 8               |
| 4                  | 32.9                                    | 84   | 16              |
| MEAN 3.25          | 100.0                                   | 89   | 11              |

Semiperishable Subsistence

| <u>LT Duration</u> | <u>% of Total<br/>Semiperishable Sample</u> | <u>% of Items Assigned to Model Type<br/>Nonseasonal</u> | <u>Seasonal</u> |
|--------------------|---|--|-----------------|
| 4                  | 9.0   | 93   | 7               |
| 5                  | 44.8  | 75   | 25              |
| 6                  | 23.7  | 87   | 13              |
| 7                  | 10.2  | 81   | 19              |
| 8                  | 12.2  | 87   | 13              |
| 9                  | 0.1   | 100  | 0               |
| 10                 | 0.0   | 100  | 0               |
| MEAN 5.72          | 100.0                                       | 82   | 18              |

**FIGURE 12**  
**FREQUENCY OF OCCURRENCE OF DEMAND**  
**SEASONALITY IN THE SUBSISTENCE COMMODITY**

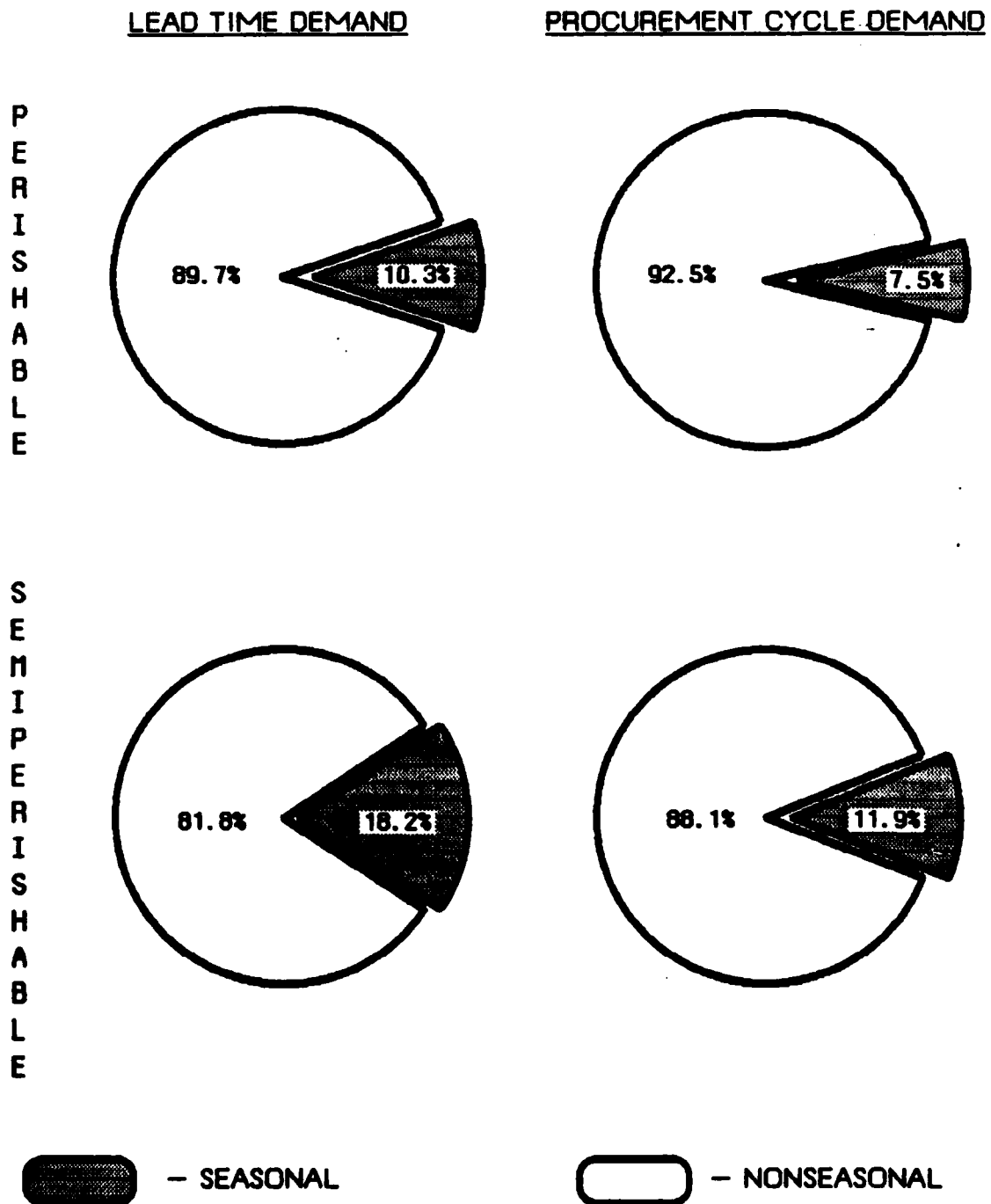


Table 23

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENTS BY  
PROCUREMENT CYCLE DURATION

Perishable Subsistence

| <u>PC Duration<br/>Months</u> | <u>% of Total<br/>Perishable Sample</u> | <u>% of Items Assigned to Model Type<br/>Nonseasonal</u> | <u>Seasonal</u> |
|-------------------------------|---|--|-----------------|
| 1                             | 100.0                                   | 93   | 7               |
| MEAN 1                        | 100.0                                   | 93   | 7               |

Semiperishable Subsistence

| <u>PC Duration<br/>Months</u> | <u>% of Total<br/>Semiperishable Sample</u> | <u>% of Items Assigned to Model Type<br/>Nonseasonal</u> | <u>Seasonal</u> |
|-------------------------------|---|--|-----------------|
| 1                             | 48.1  | 89   | 11              |
| 3                             | 50.4  | 89   | 11              |
| 4                             | 1.3   | 80   | 20              |
| 6                             | 0.2   | 100  | 0               |
| MEAN 2.06                     | 100.0                                       | 88   | 12              |

G. Areas for Further Study

Two Stage Forecasting. The authors tested two stage forecasting discussed, in Appendix C, where the forecast are adjusted for patterns in the errors. The results were promising, however, the technique can not be applied indiscriminately. When applied across all perishable items the adjusted forecasts were less accurate than the unadjusted forecasts. However, for many series the adjusted forecasts achieved 30 to 50% improvement over the unadjusted forecasts. No conclusions can be drawn without further study. The benefits of Two Stage Forecasting must be weighed against the additional data storage costs incurred. Properly applied, it may well be a valid means to achieve improved forecasting.

IV. A PROTOTYPE SUBSISTENCE DEMAND FORECASTING SYSTEM

A. Design of the Forecasting System

This section of the report describes the design of a prototype subsistence demand forecasting system based on the forecast model groups developed in Section III.



The subsistence demand forecasting system must generate a wide range of forecasts to include:

1. Fixed Forecasts (e.g., Service Requirements, Provisioning)
2. Forecast Models with Fixed Parameters (e.g., SES(.20))
3. A procedure to switch parameters and model type measure within the system based on a performance

The forecasting models in the system will be based on the final model groups in Section III with the exception that SES(.20) will be substituted for SES(.15) for perishable subsistence. The models which generate forecasts in the system are as follows:

|           |            |
|-----------|------------|
| 12-MO AVG | DLA(.20)   |
| SES(.10)  | DLA(.30)   |
| SES(.20)  | LAST LT/PC |
| SES(.30)  | LAST YEAR  |
| DLA(.10)* | ARI LAG    |

Figure 13 depicts a schematic diagram of a prototype subsistence demand forecasting system.

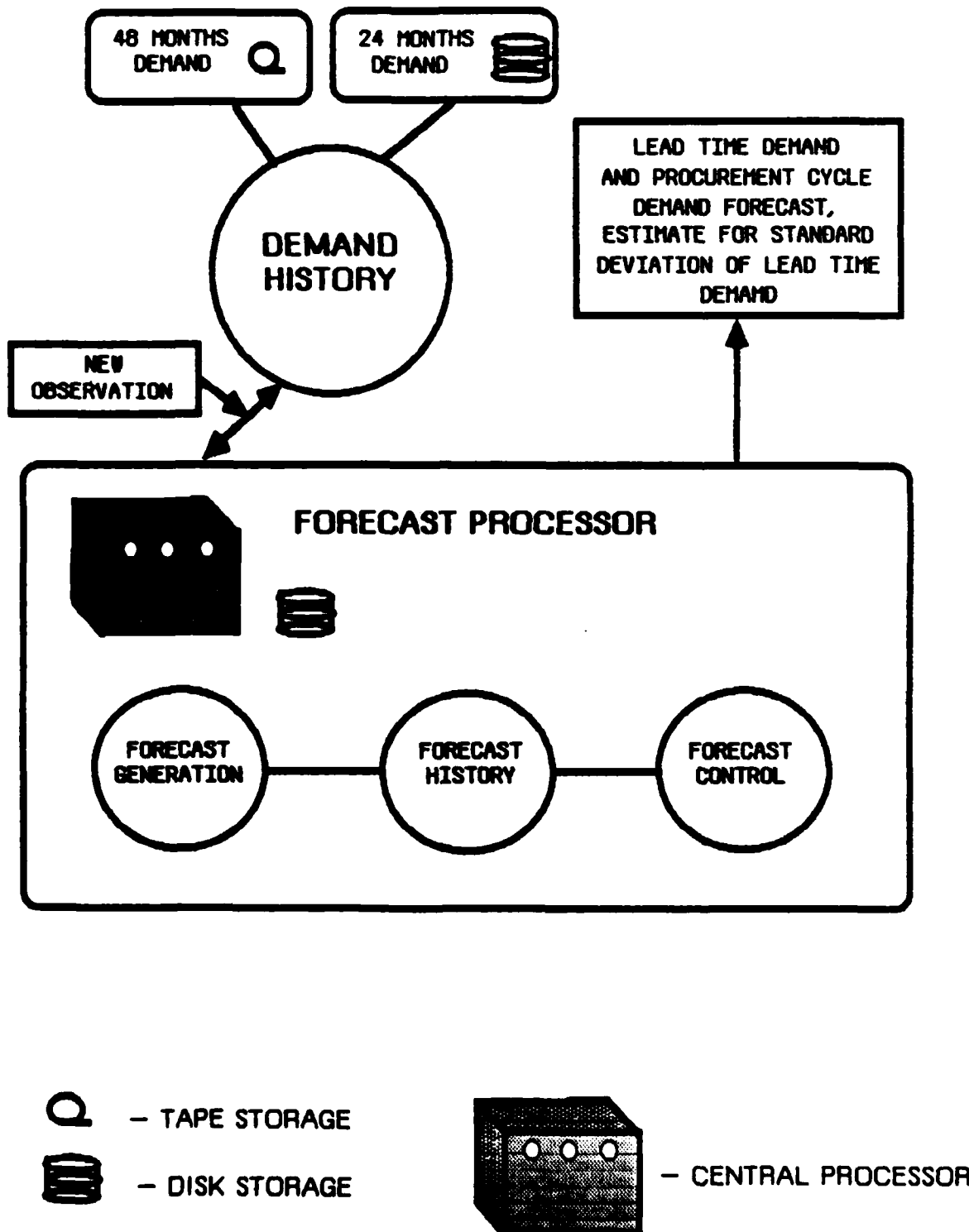
A description of each component of the system follows:

1. Demand History - DPSC presently has over 100 months of subsistence demand history available. Forty-eight (48) months of demand history are required to initialize the forecasting system. The most recent 24 months of demand history should be maintained on-line to compute the two naive forecasts and the 12-MO AVG forecast. Each month as a new demand is received, the on-line and off-line history files are updated.
2. Forecast Processor - The function of the forecast processor is to provide a forecast of the item/warehouse demand over the next lead time and procurement cycle. The forecast processor is divided into three subsystems as follows:
  - a. Forecast Generator,
  - b. Forecast History, and
  - c. Forecast Control.

The function of the forecast generator is to develop candidate forecasts for the next lead time and procurement cycle demand.

\* The DLA formula, is characterized as the one-month-ahead double exponential smoothed forecast multiplied by the lead time or procurement cycle in months

FIGURE 13  
SCHEMATIC OF PROTOTYPE  
SUBSISTENCE DEMAND FORECASTING SYSTEM



The following values are stored in the Forecast Generator to develop forecasts for single exponential smoothing, the DLA formulation and the ARI Lag Model:

The Single Smoothed Average of Monthly Demands

$$S^1(.1), S^1(.2), S^1(.3)$$

The Double Smoothed Average of Monthly Demands

$$S^2(.1), S^2(.2), S^2(.3)$$

Summations to Compute ARI Lag Forecast

$$\Sigma (F^{LM})^2, \Sigma (F^{LY})^2, \Sigma (F^{LM} F^{LY}), \Sigma F^{LM} ACT, \Sigma F^{LY} ACT$$

where:  $F^{LM}$  = Naive Monthly Forecast (i.e., current month's demand)

$F^{LY}$  = Naive Last Year Forecast

ACT = Actual Demand over Lead Time or Procurement Cycle

$\Sigma$  = Summation over the number of periods of historical demand which are maintained

Suppose S is an item with a lead time of 5 months and procurement cycle of 3 months. Let  $X_{12}, \dots, X_2$  be the most recent 11 months of on-line demand history and let  $X_1$  be the current month's demand.

The ARI LAG lead time demand forecast is generated solving the following equations for  $a_1$  and  $a_2$ :

$$a_1 (F^{LM})^2 + a_2 F^{LM} F^{LY} = (ACT) F^{LM}$$

$$a_1 F^{LM} F^{LY} + a_2 (F^{LY})^2 = (ACT) F^{LY}$$

using their values stored on the file and the current month's demand. The next ARI LAG lead time demand forecast is:

$$\begin{aligned} F_{LTD}^{LAG} &= a_1 F^{LM} + a_2 F_{LTD}^{LY} \\ &= a_1 X_1 + a_2 (X_{12} + X_{11} + X_{10} + X_9 + X_8) \end{aligned}$$

The five summations are updated and stored.

When the current month's demand is recorded, the single and double smoothed averages are updated by the formulae:

$$\text{New } S^1(\alpha) = \alpha X_1 + (1 - \alpha) S^1(\alpha)$$

$$\text{New } S^2(\alpha) = \alpha (\text{New } S^1(\alpha)) + (1 - \alpha) S^2(\alpha)$$

and stored. The single and DLA formulations are then generated, for example:

$$F_{LTD}^{SES(\alpha)} = LT * [NEW S^1(\alpha)]$$

$$F_{LTD}^{DLA(\alpha)} = LT * \left[ \left( 2 + \frac{\alpha}{1-\alpha} \right) NEW S^1(\alpha) - \left( 1 + \frac{\alpha}{1-\alpha} \right) NEW S^2(\alpha) \right]$$

The 24 months of on-line demand history are used to generate the 12 month average and naive forecasts.

$$F_{LTD}^{12-MO AVG} = LT * \frac{X_{12} + X_{11} + \dots + X_1}{12} = \frac{5}{12} \sum_{i=1}^{12} X_i$$

$$F_{PCD}^{12-MO AVG} = PC * \frac{X_{12} + X_{11} + \dots + X_1}{12} = \frac{3}{12} \sum_{i=1}^{12} X_i$$

$$F_{LTD}^{LAST LT} = X_5 + X_4 + X_3 + X_2 + X_1$$

$$F_{PCD}^{LAST PC} = X_3 + X_2 + X_1$$

$$F_{LTD}^{LAST YEAR} = X_{12} + X_{11} + X_{10} + X_9 + X_8$$

$$F_{PCD}^{LAST YEAR} = X_7 + X_6 + X_5$$

The Forecast History File provides a holding area for forecasts to be used in future forecast control. The ten forecasts:

$$F_{12-MO AVG}, F_{SES(\alpha)}, F_{DLA(\alpha)}, F_{LAST YEAR}, F_{LAST LT/PC}, F_{LAG},$$

where:  $\alpha = .1, .2, .3$

for both lead time and procurement cycle are stored in the Forecast History File until the actual lead time and procurement cycle errors can be calculated. For example, when the actual lead time demand becomes available, the  $ABSOLUTE ERROR_{LTD} = | F_{LTD} - A_{LTD} |$  is computed and passed to the Forecast Control File for the ten models.

The Forecast Control Processor is used to control the forecast selection process and provide an estimate for the standard deviation of lead time demand.

In Section III, tracking in the COMBINED model based on the smoothed MAD of .2, delivered the best forecast performance. The smoothed MAD of .2 is defined as

the single exponentially smoothed average ( $\alpha=.2$ ) of the absolute errors. The smoothed MAD will be denoted as SMAD(.2) and is defined recursively by:

$$\text{NEW SMAD}(.2) = (.2)[\text{NEW ABS}(\text{ERROR})] + .8 [\text{OLD SMAD}(.2)]$$

Due to its fine performance in controlling the COMBINED model in Section III, the SMAD(.2) method is recommended as the performance criteria for forecast selection within the Forecast Control Processor. The ten values stored in the Forecast Control Processor are as follows:

| <u>Model</u> | <u>Control Parameter</u> |
|--------------|--------------------------|
| 12-MO AVG    | <sup>1</sup> SMAD(.2)    |
| SES(.1)      | <sup>2</sup> SMAD(.2)    |
| SES(.2)      | <sup>3</sup> SMAD(.2)    |
| SES(.3)      | <sup>4</sup> SMAD(.2)    |
| DLA(.1)      | <sup>5</sup> SMAD(.2)    |
| DLA(.2)      | <sup>6</sup> SMAD(.2)    |
| DLA(.3)      | <sup>7</sup> SMAD(.2)    |
| LAST LT/PC   | <sup>8</sup> SMAD(.2)    |
| LAST YEAR    | <sup>9</sup> SMAD(.2)    |
| AR1 LAG      | <sup>10</sup> SMAD(.2)   |

Each month, as a new absolute error is passed to the Forecast Control Processor, the SMAD's are updated and the forecast with the least SMAD is chosen as the forecast for the next lead time or procurement cycle demand. An estimate for the standard deviation of lead time demand must be computed and is given by  $1.25 * \text{SMAD}(.2)$  for the chosen model.

B. System Initialization. Initialization of the system is necessary to provide initial values for the exponential smoothing and AR1 Lag model of the monthly demands and of the absolute errors. Initialization involves the use of the off-line data base. Suppose that initialization is to begin at time  $t$ . For the range of smoothing constants employed in the system, the arithmetic average of the monthly demands, 13 to 24 months ago, will serve as an initial value. The arithmetic average of the absolute errors, 1 to 12 months ago, will serve as an initial value for the SMAD calculation. Monthly demands from month 48 through 13 should be used to develop the summations for the AR1 LAG calculations. The arithmetic average, 1 to 12 months ago, can serve as the initial value for the 12-MO AVG, and naive models.

C. Decision Rules for Forecast Model Assignments to the Subsistence Commodity. Table 24 provides the model assignments for the subsistence commodity.

Table 24

DECISION RULES FOR FORECAST MODEL ASSIGNMENTS TO  
ITEM GROUPS IN THE SUBSISTENCE COMMODITY

| Established Items                                    |  | New Items  |  |
|--|--|--|--|
| Perishable   | Semiperishable                                       | 0 - 24 Months  |  |
| Appendix J   | Appendix L   | Service Requirement<br>(Fixed Forecast)  |  |
| Cross Reference<br>Listing Sorted<br>by Stock Number | Cross Reference<br>Listing Sorted<br>by Stock Number | 24 Months and Older  |  |
| Appendix K   | Appendix M   | Perishable   | Semiperishable   |
| Item Groups<br>Sorted by Model<br>Assignment         | Item Groups<br>Sorted by Model<br>Assignment         | Initially SES(.2)<br>then, switch<br>between all<br>models in fore-<br>cast system based<br>on smoothed MAD<br>(.2). | Initially SES(.2)<br>then, switch<br>between all<br>models in fore-<br>cast system based<br>on smoothed MAD<br>(.2). |

D. Implementation Considerations

The subsistence demand forecasting system must provide lead time and procurement cycle demand forecasts for about 4,000 item/warehouse records each month. The monthly updates can easily be run on DPSC mainframe computers within a 4-hour period. With modern breakthroughs in data storage and retrieval, the Forecasting System Storage Requirement is minimal, at worse.

The Forecast System provides DLA with the capability to identify, compare, and evaluate the various demand patterns encountered in the subsistence commodity. It also controls the demand forecasts when the demand pattern changes.

V. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

o Seasonality is an important factor in subsistence demand forecasting. Seasonality of lead time demand occurs about 14% of the time for centrally stocked Subsistence items. Seasonality is more prevalent in the semiperishable (18%) versus perishable (10%) category. Improvements in forecast accuracy were generally much greater for items with seasonal patterns than for those with nonseasonal patterns (Tables 20 and 21).

o Demand forecasting for nonseasonal subsistence items can be significantly improved. Although the larger reduction in forecast error can be achieved for seasonal items, a reduction can also be achieved for nonseasonal items (Tables 20 and 21). The nonseasonal component of the Final Model group

reduced forecast error (measured by RMSE) by 14.7% over the lead time and 11.6% over the procurement cycle for nonseasonal perishable items. For nonseasonal semiperishable items, the reductions were 8.6% and 6.7%, respectively.

- o Reduction in safety levels and "stockout cost" are possible. Reductions in the standard deviation of lead time demand will surely reduce the safety level stock held for subsistence recently valued at around \$95 million (end FY 84). Also the costs of "stockout", both tangible such as special processing and impact on substitute item demand and intangible, such as customer satisfaction, will be more easily managed.

- o A Forecasting System based on a group of models tested in this study can identify, compare, evaluate, and control subsistence demand patterns. Section IV describes a prototype forecasting system for the subsistence commodity. This system is based on a blend of theoretical and practical considerations. The system is designed to provide fixed forecasts, forecasts based on models with fixed parameters, and forecasts selected by performance measure. The system is relatively simple and easy to implement.

#### B. Recommendations

- o The Executive Director for the Directorate of Supply Operations should take the following actions as a result of this study:

- oo Direct that the prototype Forecasting System designed in this report be used as the basis for the Functional Description under the Defense Integrated Subsistence Management System (DISMS). Identify resources for the purposes of implementation and monitor performance.

- oo Direct the incorporation of the prototype Forecasting System into the existing subsistence requirements computation system. This would serve as an independent validation of the Forecasting System and lend credence to its implementation into DISMS.

- oo Direct the computer software generated in the design of the Forecasting System by maintained by DISMS for future use.

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